Exploring the Interaction of Abstraction and Engagement in Learning Programming Concepts

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Tiivistelmä — Referat — Abstract

The design of instructional material affects learning from it. Abstraction, or limiting details and presenting difficult concepts by linking them with familiar objects, can limit the burden to the working memory and make learning easier. The presence of visualizations and the level to which students can interact with them and modify them also referred to as engagement, can promote information processing. This thesis presents the results of a study using a 2x3 experimental design with abstraction level (high abstraction, low abstraction) and engagement level (no viewing, viewing, presenting) as the factors. The study consisted of two experiments with different topics: hash tables and multidimensional arrays. We analyzed the effect of these factors on instructional efficiency and learning gain, accounting for prior knowledge, and prior cognitive load.

We observed that high abstraction conditions limited study cognitive load for all participants, but were particularly beneficial for participants with some prior knowledge on the topic they studied. We also observed that higher engagement levels benefit participants with no prior knowledge on the topic they studied, but not necessarily participants with some prior knowledge. Low cognitive load in the pre-test phase makes studying easier regardless of the instructional material, as does knowledge on the topic being studied.

Our results indicate that the abstractions and engagement with learning materials need to be designed with the students and their knowledge levels in mind. However, further research is needed to assess the components in different abstraction levels that affect learning outcomes and why and how cognitive load in the pre-test phase affects cognitive load throughout studying and testing.

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Social and professional topics - Computer science education,
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Avainsanat — Nyckelord — Keywords

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Muita tietoja — övriga uppgifter — Additional information

Contents

1 Introduction

Computer programs run our society, and the software industry is a big part of our economies. Teaching programming is, therefore, essential to meet the growing demand for coders, and more and more students choose to study coding at university level. An essential part of any university programming course, whether held online as a MOOC or as a traditional lectured course, are the instructional materials offered to students. Instructional materials often combine visual and interactive elements such as visualizations with text and exercises and are provided either as hard copies on paper or as online resources.

The design of instructional material can affect how well students can learn from it, so care must be taken to design the instructional materials so that they promote learning. To do this, it is necessary to take into account how our memory works. Information is processed in the working memory before it is stored as processed data structures, schemata, in the long-term memory. The working memory is very limited in capacity. The working memory resources required to handle information are referred to as cognitive load [NRA$^+$02, SvMP19], which can be caused by the information itself or the way the information is presented. Too high cognitive load can limit the working memory resources available for effective information processing and make learning more difficult. Previous research suggests what cognitive load can be limited by using abstractions [vMJKK12]. With abstractions, we refer to the way information is presented - highly abstract material presents information in general terms linking it to concepts familiar from our everyday environment. Less abstract material presents the information in terms of field-specific visuals and concepts.

Previous research also suggests that engagement can promote information processing [NRA$^+$02, MLK07]. Engagement refers to the degree to which students can interact with instructional material and modify it - the degree to which the instructional material guides students to react to and use the information rather than just looking at it. Better engagement can be achieved by using visual elements, such as visualizations, and different interactive features as a part of instructional materials.

Instructional materials can be compared in terms of their instructional efficiency. Instructional efficiency is a measure for how easily students are able to achieve good learning outcomes using the instructional material [VGP08]. It is calculated from the cognitive load of studying instructional material, achieved learning outcomes, and the cognitive load of using the learned information (test cognitive load) [TP04].

In this thesis, we examine the combined effect of engagement and abstraction on the instructional efficiency of online instructional material teaching programming concepts. We also assess how cognitive load before studying and prior knowledge on the topic being studied affect the instructional efficiency, as well as how engagement and abstraction affect learning gain.

2 Background

In this section, we discuss the theoretical frameworks on which our research builds upon. We have included the relevant theories on learning and cognition, designing instructional materials, and evaluating instructional efficiency.

2.1 Learning and cognition

2.1.1 Categories of knowledge

Two overlapping classifications can describe human knowledge: Biologically primary knowledge versus biologically secondary knowledge [SS06] and domain-general versus domain-specific knowledge [Swe15].

Biologically primary knowledge is the knowledge that we have specifically evolved to acquire, such as speaking our native language and walking. It is often acquired unconsciously and does not need to be taught. Domain-general knowledge refers to general skills essential to human functioning in all domains of life, such as problem-solving. Biologically primary knowledge is often domain-general.

Biologically secondary information correspondingly is the knowledge we explicitly have to study either independently through instructional material or instruction in education and training contexts, such as geometry or coding in Java. Without appropriate institutions and procedures, secondary knowledge will not be acquired by most members of a society [SvMP19, SS06]. Biologically secondary knowledge is often domain-specific, category for knowledge about a specific domain, such as mathematics [Swe15].

2.1.2 Human cognitive architecture

Human cognitive architecture is responsible for processing and storing information. The principles of this knowledge acquisition will be described in detail in section 2.1.3. In this section, we will describe the details of the human cognitive architecture.

The human cognitive architecture consists of the sensory memory, the working memory with limited capacity to process novel information [Mil56], and the long-term memory with almost immeasurable capacity to hold processed, structured information [PTTVG03, HEH09]. The human cognitive architecture is depicted in Figure 1.

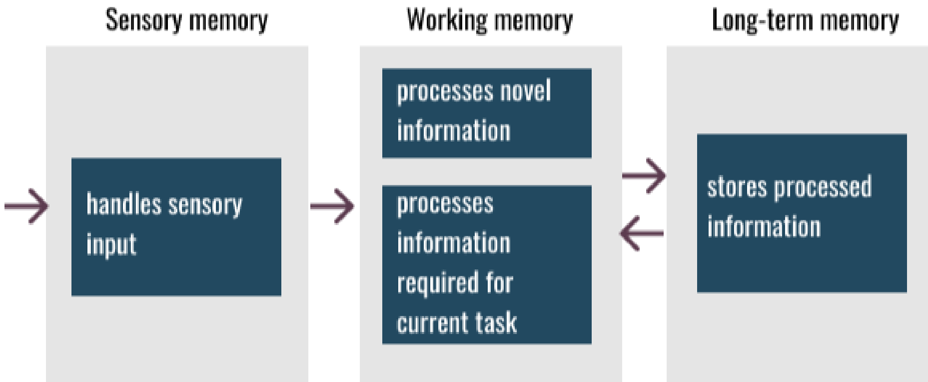


Figure 1: Human cognitive architecture consist of sensory memory, the working memory and the long term-memory.

The sensory memory first handles new information. The information that is paid attention to, either consciously or unconsciously, is passed to the working memory to be processed. Lastly, information is passed to the long-term memory for storage [Swe16]. This process is depicted in Figure 2. It shows how information moves from the outside world to the sensory memory, and then to working memory and the long-term memory. Effective cognitive processing is required to pass information from sensory memory through to the long-term memory [HEH09].

In some representations of the human cognitive architecture, the sensory memory is seen as part of the working memory [SVMP98]. According to these representations working memory consists of three partially separate processors: the "visual-spatial scratchpad" which handles visual information, the "phonological loop" which handles auditory information, and the central executive that manages the two sensory processors [PTTVG03].

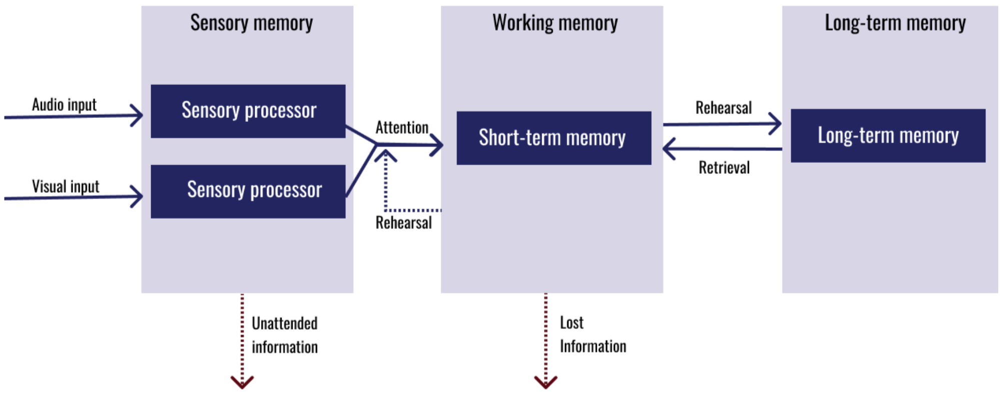


Figure 2: Description of how the sensory memory, the working memory and the long-term memory process information.

However, no matter how the sensory memory is represented, it is agreed upon that the two different sensory modalities, audio and visual, are handled by different processors, which can process information separately from each other. As these processors are partially separate, the capacity of the working memory to process information can be increased by using multiple processors at once.

2.1.3 Principles of acquiring knowledge

Five principles govern the acquisition of domain-specific biologically secondary knowledge [SvMP19].

1. **The information store principle**. Our information processing system contains a central store of information. Due to the complexity of our environment, and thus the amount of knowledge we have to store about our environment, this central store is almost immeasurably vast. Our central store is in long-term memory. The information in our long-term memory governs the bulk of our cognitive activities. [PMB10, SS06]

2. **Randomness as genesis principle**. New knowledge is created through problem-solving – selecting moves within the problem domain as it is understood, and testing their effectiveness [WLMS12].

3. **The borrowing and reorganizing principle**. We do not create most of our knowledge ourselves but borrow it from other people's long-term memories through listening, reading, observing others, and other interaction. We

reorganize this knowledge through the lens of our long-term memory, which might result in random changes [WLMS12].

4. **The narrow limits of change principle**. Effective changes to long-term memory occur slowly and incrementally [PMB10]. We process novel information in our working memory before it is stored in our long-term memory [Swe15]. Working memory can handle only a limited number of new pieces of information at once, radically limiting the changes to the information store that can be made at once [Swe15].

5. **The environmental organizing and linking principle**. Information we have processed and organized in the working memory, which is stored in the long term memory, can be retrieved to the working memory and handled as one unit of information. When necessary, unlimited amounts of organized information in long-term memory can be brought into working memory to organize the environment and determine actions that are appropriate to the environment [SS06].

2.1.4 Cognitive load

The working memory, the memory used to process new information, has limited capacity. The limited capacity puts limits on the amount of information that can be processed at once. It also leads to the possibility, that if either the information itself or stimulus extrinsic to the information being processed overburdens the working memory, the information cannot be processed effectively. [PMB10]

Cognitive load refers to the burden to the working memory from processing information. Although sometimes intrinsic and germane cognitive load are bundled together as cognitive load caused by processing information, in the context of this work, we refer to them as separate classes of cognitive load. Cognitive load can be caused by properties of the information itself (intrinsic cognitive load), properties of the instructional material (extrinsic cognitive load), or the burden to the working memory caused by processing information (germane cognitive load). [MBCA19]

- Intrinsic cognitive load. Intrinsic cognitive load is determined by the complexity of the learning task and results from element interactivity - the number of interacting information elements belonging to a learning task [MBCA19]. Prior knowledge of the information reduces intrinsic cognitive load, as parts of the information have already been structured into schemata, which can be handled in the working memory as one element [PMB10].

- Extrinsic cognitive load. Extrinsic cognitive load is cognitive load resulting from the presentation of the information. The design of instructional material can directly manipulate this cognitive load [Swe15].

- Germane cognitive load. Germane cognitive load is the cognitive load caused by processing information [MBCA19]. The goal of instructional material should be to decrease extrinsic cognitive load to make working memory capacity available for germane cognitive load.

Learning is compromised when the sum of the intrinsic, extrinsic, and germane cognitive load exceeds the available working memory capacity. Ideally, instructional material should reduce extrinsic cognitive load and use the liberated cognitive resources to promote germane cognitive load [PMB10].

2.1.5 Schema theory

Knowledge is stored in our information store, our long-term memory, as structured information constructs called schemata. Schemata are cognitive structures that represent a particular stimulus or problem domain [TCD78]. Schemata are abstractions of information, and they represent knowledge as patterns of relationships between elements. Schemata are used to categorize information according to their use and store appropriate solutions for problems [Mar09].

For example, a computer programmer might have a schema on which kind of loop to use in which kind of iteration task. It can be retrieved from long-term memory when needed and allows for solving iteration problems effectively. This process is depicted in Figure 3. It details how stimulus from the environment leads either to the retrieval of a schema relevant to the current situation from the long term memory or if there is no existing, relevant schema, to the creation of a new schema.

The schemata in our long-term memory govern the way we acquire new knowledge. If we do not have a schema for handling a certain situation or task, we apply problem-solving strategies to find appropriate solutions and construct a new schema for the problem domain. If we have a relevant schema, we recall the schema to our working memory.

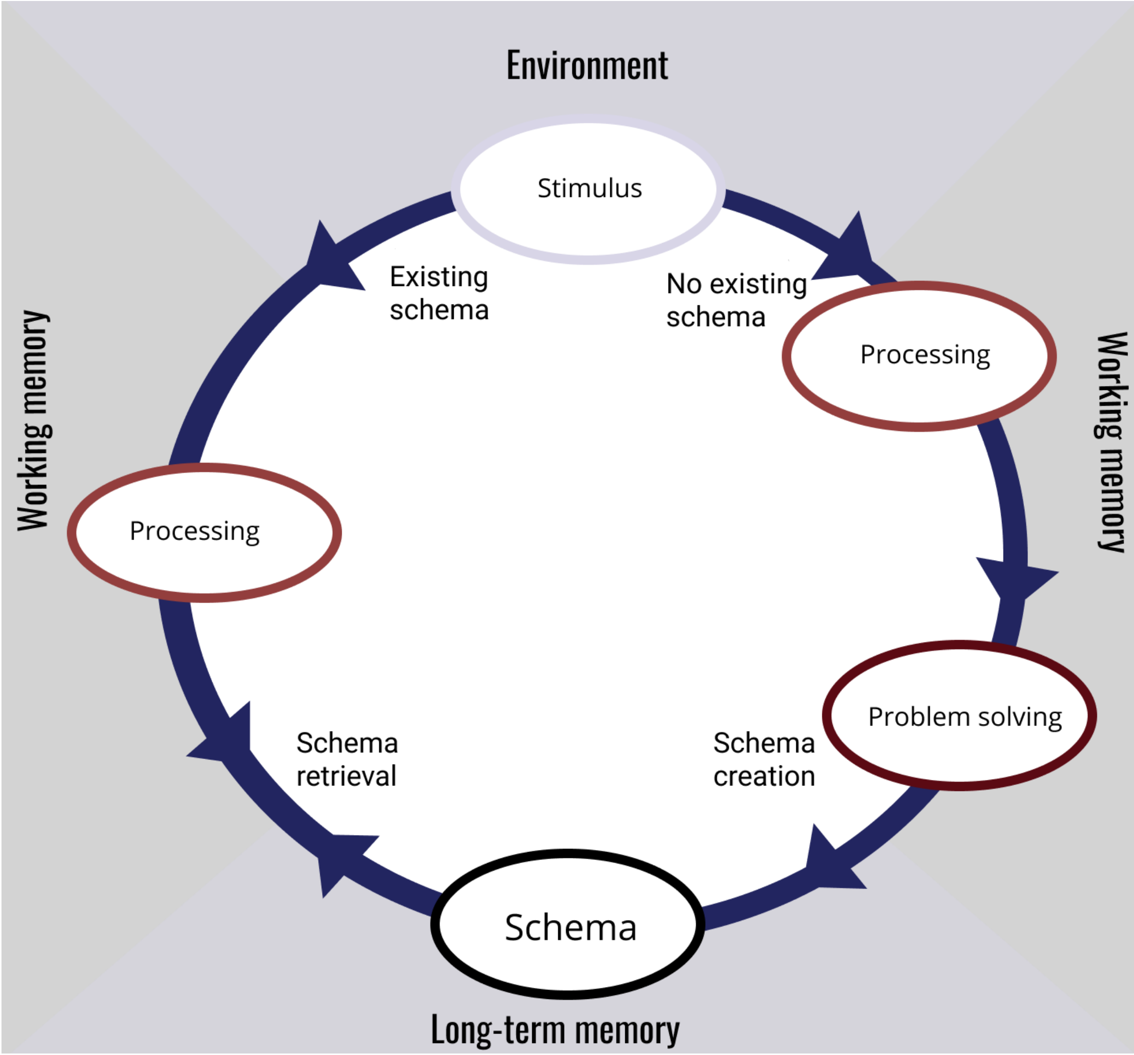


Figure 3: Stimulus from the environment leads to either retrieval of a relevant schema from the long term memory or creation of a new schema.

Any new information is always processed in terms of our existing schemata [Mar09] – we can then either remodel a schema to incorporate any new relevant information, or if the new information does not fit within our existing schema, reject the new information [Mar09, PMB10]. This process is detailed in Figure 4.

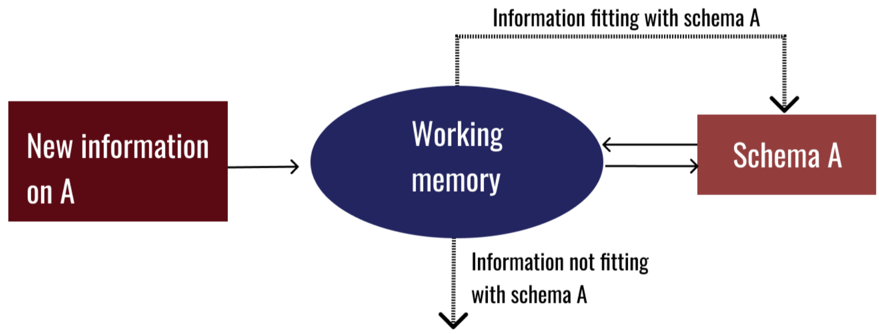


Figure 4: New information is processed in terms of our existing schemata, and information not fitting within them is rejected.

For example, the computer programmer might learn about a new kind of a loop, and restructure their old loop schema to accommodate this new loop. Schemata are also joined together to form larger schemata in a process called chunking. A novice programmer first develops separate small schemata for variables and conditional statements as well as programming problems that require iteration. With more experience, these schemata can be joined together into a loop schema, which contains all the previous schemata as one schema unit, and can be handled in the working memory as one unit of information [Mar09].

With repetitive use, schemata become automated. An automated schema does not have to be processed consciously. For example, many of us reading this text have an automated schema for understanding how letters form words, and we do not have to process text letter by letter automatically [Mar09].

2.2 Instructional materials

In subsection 2.1, we have discussed learning and human cognitive architecture. Biologically secondary, domain-specific knowledge is acquired through instruction in educational settings. Different instructional materials are used in educational contexts to transfer information. The human cognitive architecture and the five principles of knowledge acquisition discussed in sections 2.1.2 and 2.1.3 govern how we acquire new knowledge, and in order of instructional material to be effective, they have to be taken into account. Instructional material should aim to decrease extraneous cognitive load and promote germane cognitive load. Complex content with many interacting elements can also be presented in ways that reduce element interactivity and thus reduces intrinsic cognitive load.

Instructional material effects on cognitive load have been identified [VGP08]. Some of these effects include the modality effect, which states that working memory capacity can be increased by using both visual and auditory working memory rather than either processor alone to lessen the extrinsic cognitive load from instructional materials [SvMP19]. Germane cognitive load can be increased by emphasizing the sub-goal structure of a learning task. This allows learners to self-explain why specific steps belong together, increasing germane cognitive load [vMJKK12]. Intrinsic cognitive load can be managed using the Low-to-High-Fidelity strategy, where the number of interacting information elements is gradually increased by increasing the fidelity of the material [vMJKK12]. This aids novices with no existing schema on the topic. Low-fidelity material with less interacting elements causes novices less cognitive load. A table detailing all the identified effects can be found in Appendix 1. Principles for presenting multimedia instructional material in a way that supports learning have also been identified [May09]. These principles are detailed in Table 1.

Multimedia design principles	
Coherence Principle	Learning is improved when extraneous material is excluded rather than included [May09]. Extraneous material contains interesting but irrelevant words, pictures, sounds and music, and unnecessary words and symbols [May09].
Signaling Principle	Learning is improved when the attention of the student is guided towards important information using signaling techniques such as outlines, headings, and spoken emphasis on keywords [May05].
Redundancy Principle	Students learn better from graphics and narration than from graphics, narration, and printed text [May09].
Spatial Contiguity Principle	Students learn better when corresponding words and images are presented near rather than far from each other on the page or screen [May02].
Temporal Contiguity Principle	Students learn better when corresponding words and pictures are presented simultaneously rather than successively [May02].
Segmenting Principle	Learning is improved when a multimedia message is presented in user-paced segments rather than as a continuous unit [May09].

Pre-training Principle	Learning from multimedia instructional material is improved when the student is equipped with knowledge, which makes understanding the multimedia message easier [May05].
Modality Principle	Students learn better from material combining visual- and audio elements than from visual material alone [May02].
Multimedia Principle	Students learn better from material combining visual- and audio elements than from audio material alone [May09].
Personalization Voice and Image Principle	Learning from multimedia presentations is improved when words are in conversational style rather than formal style [May09].

Table 1: Principles for presenting multimedia instructional material in a way that supports learning.

The identified cognitive load effects and the principles of creating effective multimedia instructional material together give a detailed picture of how to create multimedia instructional material that allows for effective learning.

2.2.1 Engagement taxonomy

In computer science education, visualizations are used as a part of multimedia instructional material to graphically illustrate various concepts of computer science. The visualization engagement taxonomy argues that learning from a visualization is improved when the visualization engages students in an active learning activity [NRA+02]. The engagement taxonomy has six levels of engagement between a student and a visualization [MLK07]. The levels of engagement are detailed in Table 2.

In the context of the engagement taxonomy, learning outcomes are measured in terms of Bloom's taxonomy of understanding [NRA+02]. Bloom's taxonomy of understanding contains six categories of cognitive skills ranging from lower-order skills that require less cognitive processing to higher-order skills that need deeper learning and a higher degree of cognitive processing [Ada15].

Engagement taxonomy	
No viewing	There is no visualization.
Viewing	Visualization is passively viewed.
Responding	Student is prompted to answer questions concerning the visualization.
Changing	Student is able to modify the visualization.
Constructing	Student constructs their own visualization.
Presenting	Student presents the visualization they have constructed to an audience for feedback and discussion.

Table 2: Levels of engagement identified in the engagement taxonomy.

The engagement taxonomy states that higher levels of engagement between a student and a visualization lead to higher levels of understanding on Bloom's taxonomy of understanding [NRA$^+$02].

2.2.2 Evaluating instructional efficiency

In sections 2.2.1 - 2.2.3, we have discussed the properties of effective instructional materials. Effective instructional material decreases extraneous cognitive load to free cognitive resources for germane cognitive load through the way information is presented. Instructional material containing visualizations should also promote engagement between a student and the visualization to promote learning.

The cognitive load caused by instructional material is an important factor in its efficiency. Multiple ways to measure cognitive load have been proposed. Paul Chandler and John Sweller deducted cognitive load from study task completion times [CS91]. Different subjective rating scales have been used to ask subjects to rate the cognitive load of a task [Har06, PTTVG03, MDG14, PVMA94]. Dual-task methodology, or requiring subjects to complete two tasks simultaneously while measuring task performance, has also been used [BPL03]. Different physiological measures, such as heart-rate variability and pupillary response, have also been used to measure cognitive load [PTTVG03].

The cognitive load caused by a learning task and learning outcome measures can be used to calculate instructional efficiency scores [VGP08]. In this work, we used the adapted formula by Tuovinen and Paas [TP04]. The formula was selected because it incorporates the cognitive load both from studying the material and taking the test.

The first instructional efficiency formula

$$Efficiency = \frac{zP_{test} - zE_{test}}{\sqrt{2}} \quad (1)$$

where zP_{test} is a normalized test performance measure, and zE_{test} is a normalized test cognitive load measure, calculates the achieved learning outcomes to the expended mental effort of taking a test.

The formula was later modified to

$$Efficiency = \frac{zP_{test} - zE_{learning}}{\sqrt{2}} \quad (2)$$

to calculate achieved learning outcomes to expended mental effort of studying.

Tuovinen and Paas further adapted the formula to accommodate both learning and test measures [TP04].

$$Efficiency = \frac{zP_{test} - zE_{learning} - zE_{test}}{\sqrt{3}} \quad (3)$$

The instructional efficiency measure can be used to measure the quality of learning outcomes - "The acquisition of more (less) efficient cognitive schemata is indicated by combinations of high (low) performance and low (high) mental effort" [VGP08].

3 Study design

In this section, we detail our research questions and discuss the context of the study - the programming course the study was conducted on.

3.1 Research questions

In this work, we seek to determine the combined effect of abstraction and engagement on the instructional efficiency of instructional materials in the context of an online university programming course.

We define abstraction in terms of the fidelity of the instructional material, and the way the instructional material is presented. Highly abstract instructional materials limit the number of details given to the student, and visually display the topic in a way closer to everyday real-world items such as presenting Java lists as a list on notepaper. Conversely, less abstract instructional materials offer more details to the student. Less abstract material also visually present the matter in a way either closer to the reality of the subject (such as code examples) or in a way closer to traditional visual representations of the item, such as presenting Java lists the way they are traditionally drawn in computer science diagrams.

The research questions we seek to answer are:

RQ1 How do engagement and abstraction together affect the instructional efficiency of instructional material?

RQ2 Does prior knowledge on the topic being studied affect the instructional efficiency of instructional material?

RQ3 How does cognitive effort expended prior to studying affect the instructional efficiency of instructional material?

With the first research question, we seek to determine the combined effect of abstraction and the engagement on the instructional efficiency of instructional material. We hypothesize that as element interactivity increases as the abstraction level decreases, the modality effect becomes more pronounced for the lower abstraction levels. This leads to higher instructional efficiency on higher engagement levels on lower abstraction levels.

With the second question, we explore the role of prior knowledge on instructional efficiency. We hypothesize that novices with no prior schemata on the topic achieve better learning outcomes from higher abstraction levels containing text and images closer to everyday situations for which novices have schemata for. We further hypothesize that for a student with prior knowledge on the studied topic, the opposite is true and that due to expertise reversal effect, the lower abstraction levels and less visualized information leads to better instructional efficiency.

With the third question, we seek to determine the role of cognitive effort expanded before studying on instructional efficiency. We hypothesize that as cognitive effort expanded before studying affects the cognitive resources available, high cognitive effort before studying leads to higher instructional efficiency of instructional material, which causes the least cognitive load - highly abstract material on viewing or responding engagement levels.

3.2 Context

3.2.1 Programming course

The data used in the experiment comes from two programming courses held at the University of Helsinki in autumn 2019. Java Programming II is an advanced Java programming course containing both lectures and self-study. Programming MOOC 2019 is the same advanced Java programming course but offered as an online-only version. Both courses use the same online instructional material.

The course covers the basics of Object-oriented programming in Java, including basic concepts such as variables, loops, classes, and methods as well as more advanced topics such as testing, user interfaces, three-dimensional data, and hash maps.

In week six of the course, the students are introduced to the idea of hash maps. They get familiar with using Java HashMap objects by being asked to make a new HashMap object, add new key-value -pairs to the hash map, and find a value of a key in the hash map. The experiment was run in week 11 of the course. This week the students are introduced to the implementation of a hash map using Java arrays and ArrayLists. This week students are also introduced to multidimensional arrays for the first time, although they have previously used one-dimensional arrays in multiple parts of the course.

The primary instructional material for the course is an online workbook. The online document contains text sections detailing programming concepts blended with questionnaires and programming exercises. Students are expected to study a part of the material weekly, answer to the quizzes, and return the programming exercises before advancing to the next part the following week. The study took place on week 11 of the course. The topics of this part were generic type parameters, ArrayList and hash maps, randomness in programming, and multidimensional data. The instructional material contained a chapter of text for each topic blended with code examples, quizzes, and programming exercises. The study materials were embedded in chapters 2 and 4; ArrayList and hashmaps and multidimensional data.

Java Programming II is a timed course. A new chapter of instructional material is published weekly, and students have a week to study the material and complete the exercises it contains. Programming MOOC 2019 is a self-paced course, the deadline for the whole course being at the end of the year. All chapters of the instructional material were published at once, and students could proceed on studying the material and completing the exercises at their own pace.

3.2.2 Data gathering

When students create an account for the online instructional material, they are asked for permission to use their data for research. Students are informed that if they agree, data can be collected about their use of the online instructional material, their quiz answers, and their grades. Only data from students who had given the permission was used for this study.

The quiz answer data was collected using the questionnaire system the course uses for all questionnaires. We collected the usernames and student identification numbers of participating students, as well as their responses to the pre- and post-test questionnaires.

4 Methodology

In this section, we describe our study methodology. We detail the study design and discuss the participants of the study, as well as the study materials - the pre- and post-test questionnaires and the instructional materials. We also discuss the study procedure, the data we collected and the statistical analyses conducted to answer our research questions.

4.1 Participants and design

123 students currently studying the Java Programming II advanced Java programming course at the University of Helsinki or taking the Programming MOOC 2019 advanced online Java programming course participated in the study. More students were studying both courses, but 41 students studying the MOOC and 82 students studying the lectured course allowed data collection for research and participated in the study.

The study followed a 3 x 2 experimental design with abstraction level (high abstraction, low abstraction) and engagement level (no viewing, viewing, responding) as the two factors. The factors are detailed in tables 3 and 4.

Engagement levels	
No viewing	No visualization. Text explaining the concept.
Viewing	Static visualization combining text and static images
Responding	Interactive slideshow explaining the concept with text and images blended with questions.

Table 3: Engagement levels

Abstraction levels	
Level 1	High abstraction. Limited technical details. Material tied to concepts close to real world situations.
Level 2	Low abstraction. Contains technical details. Visualizations close to traditional visualizations on the topic.

Table 4: Abstraction levels

The treatment conditions are detailed in Table 5.

Participants were randomly assigned to two treatment conditions - one for the hash table experiment and one for the multidimensional arrays experiment. The process of dividing students from the two courses to the six treatment conditions is detailed in Figure 5.

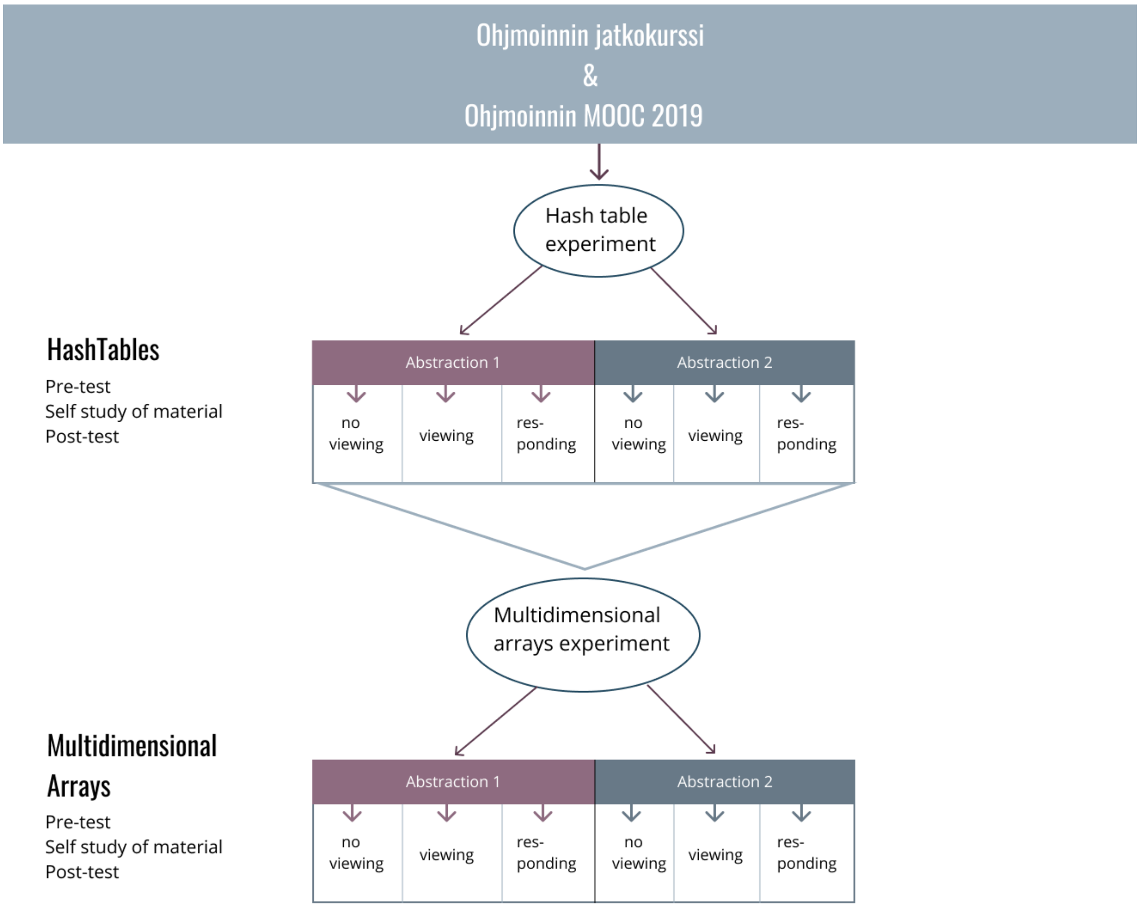


Figure 5: Students from the two courses are divided into 6 treatment conditions

Sizes of the treatment conditions are detailed in Table 5. Table 5 also details the numerical codes of each treatment condition, which will be used to refer to them the rest of the thesis. The difference in the number of participants between the hash table experiment and the multidimensional arrays experiment can be explained by students not completing the work for the week the study was run.

Code	Treatment condition	Total	HT	MD
1	high abstraction - no viewing	31	16	15
2	high abstraction - viewing	27	15	12
3	high abstraction - responding	47	24	23
4	low abstraction - no viewing	51	30	21
5	low abstraction - viewing	37	16	21
6	low abstraction - responding	42	20	22

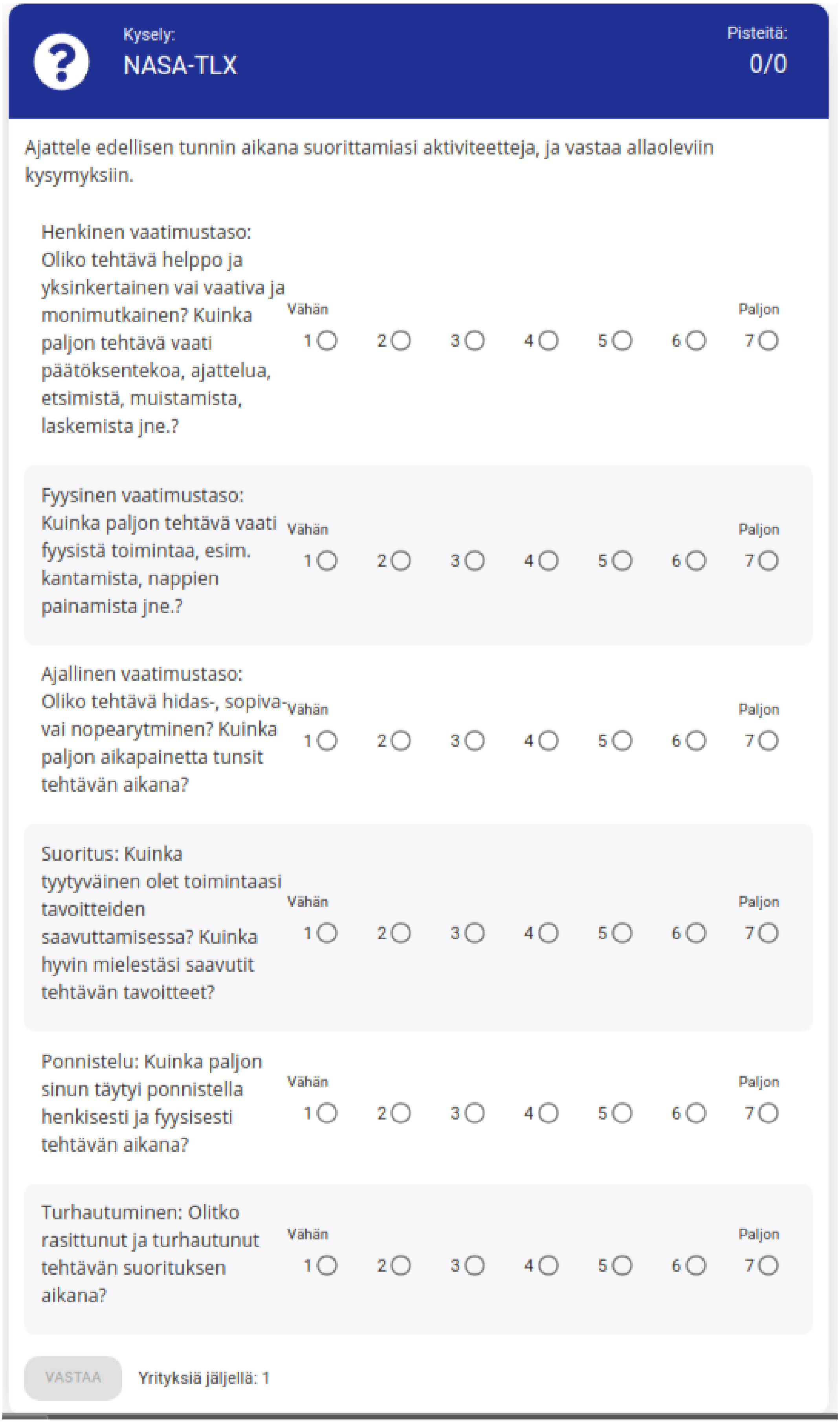
Table 5: Treatment conditions and their numerical codes and number of participants in each treatment condition for Hash table experiment (HT), Multidimensional arrays experiment (MD) and in total.

4.2 Materials

The materials consisted of two sets of instructional materials embedded in the course's online workbook, two pre-test questionnaires, and a post-test questionnaire.

4.2.1 Pre-test

The pre-test questionnaires consisted of a NASA-Task Cognitive Load Index questionnaire (NASA-TLX) and a pre-test questionnaire measuring participants' knowledge level and cognitive load. The NASA-TLX [Har06] questionnaire asks participants to rate the mental and physical effort they have expanded within the last hour before the experiment. The NASA-TLX questionnaire was translated to Finnish from the original English. Both the original questionnaire and the Finnish translation can be found from appendixes 2 and 3. Figure 6 shows the NASA-TLX questionnaire as it was presented in the experiment.



Kysely:
NASA-TLX

Pisteitä:
0/0

Ajattele edellisen tunnin aikana suorittamiasi aktiviteetteja, ja vastaa allaoleviin kysymyksiin.

	Vähän						Paljon
Henkinen vaatimustaso: Oliko tehtävä helppo ja yksinkertainen vai vaativa ja monimutkainen? Kuinka paljon tehtävä vaati päätöksentekoa, ajattelua, etsimistä, muistamista, laskemista jne.?	1 ◯	2 ◯	3 ◯	4 ◯	5 ◯	6 ◯	7 ◯
Fyysinen vaatimustaso: Kuinka paljon tehtävä vaati fyysistä toimintaa, esim. kantamista, nappien painamista jne.?	1 ◯	2 ◯	3 ◯	4 ◯	5 ◯	6 ◯	7 ◯
Ajallinen vaatimustaso: Oliko tehtävä hidas-, sopiva- vai nopearytminen? Kuinka paljon aikapainetta tunsit tehtävän aikana?	1 ◯	2 ◯	3 ◯	4 ◯	5 ◯	6 ◯	7 ◯
Suoritus: Kuinka tyytyväinen olet toimintaasi tavoitteiden saavuttamisessa? Kuinka hyvin mielestäsi saavutit tehtävän tavoitteet?	1 ◯	2 ◯	3 ◯	4 ◯	5 ◯	6 ◯	7 ◯
Ponnistelu: Kuinka paljon sinun täytyi ponnistella henkisesti ja fyysisesti tehtävän aikana?	1 ◯	2 ◯	3 ◯	4 ◯	5 ◯	6 ◯	7 ◯
Turhautuminen: Olitko rasittunut ja turhautunut tehtävän suorituksen aikana?	1 ◯	2 ◯	3 ◯	4 ◯	5 ◯	6 ◯	7 ◯

VASTAA Yrityksiä jäljellä: 1

Figure 6: Pre-test NASA-TLX questionnaire in Finnish as it was presented in the study. The English version can be found from appendix 2

The pre-test questionnaire measured participants' prior knowledge, self-evaluated prior knowledge, and pre-test cognitive load. It contained a 3 question multiple-choice questionnaire of the topic of the instructional material, a self-evaluation of current knowledge level (rating scale from 0 to 2), and self-evaluation of cognitive load of answering the pre-test questionnaire. For evaluating cognitive load, we used the "unidimensional 9-point symmetrical category rating scale" developed by Paas [PVMA94]. The scale asks participants to rate the mental effort expended during a task from 1 to 9 ("ranging from 1-very, very low mental effort to 9-very, very high mental effort" [PVMA94]).

4.2.2 Instructional materials

The experiment instructional materials were embedded in the online workbook the participants had been using throughout the course. The instructional materials were shown in place of two sections of text on two chapters of week 11 of the advanced Java programming courses. The instructional materials delivered a lesson about the topic of the chapter, either hash tables or multidimensional arrays.

For hash tables, the topics of the section were the implementation of a hash table in Java, the role of hash values and hash functions, adding a new key-value pair to a hash table, and finding the value of a key from a hash table. For multidimensional arrays, the topics were the nature of multidimensional data, the structure of a multidimensional array in Java, and using multiple indexes to find a value from a multidimensional array. All six treatment conditions were tested with both chapters.

No viewing condition with both abstraction conditions contained a textual explanation of the data structure. Image of a section of high abstraction level no viewing condition for the multidimensional arrays test is displayed in Figure 7.

Toistaiseksi olemme käsitelleet vain yksiuloitteista tietoa yksiuloitteisissa taulukoissa, joissa indeksi kertoo tiedon sijainnin sen ainoassa ulottuvuudessa.

Voimme käsitellä myös moniuloitteista tietoa moniuloitteisissa taulukoissa. Jos esimerkiksi haluaisimme tarkastella koirien painoja ikäryhmittäin, tarvitsisimme kaksi ulottuvuutta: ikäryhmät ja painon.

Tässä tapauksessa tarvitsemme taulukon ikäryhmille, jonka jokainen alkio sisältää taulukon painoja kyseisessä ikäryhmässä. Yksittäisen painon saisimme käsiimme kahden indeksin avulla: indeksin ikäryhmätaulukossa ja indeksin painotaulukossa.

Jos taas haluaisimme tarkastella koirien eläinlääkärinkäyntejä vuodessa ikä- ja painoryhmittäin, tarvitsemme jo kolme ulottuvuutta: iän, painon ja eläinlääkärikäyntien määrän vuodessa.

Figure 7: No viewing condition as it was presented in the study material

The viewing condition with both abstraction conditions contained a static pdf embedded to the instructional materials which explained the topic combining text and images. Section of the viewing condition on low abstraction level for the multidimensional arrays test is displayed in Figure 8.

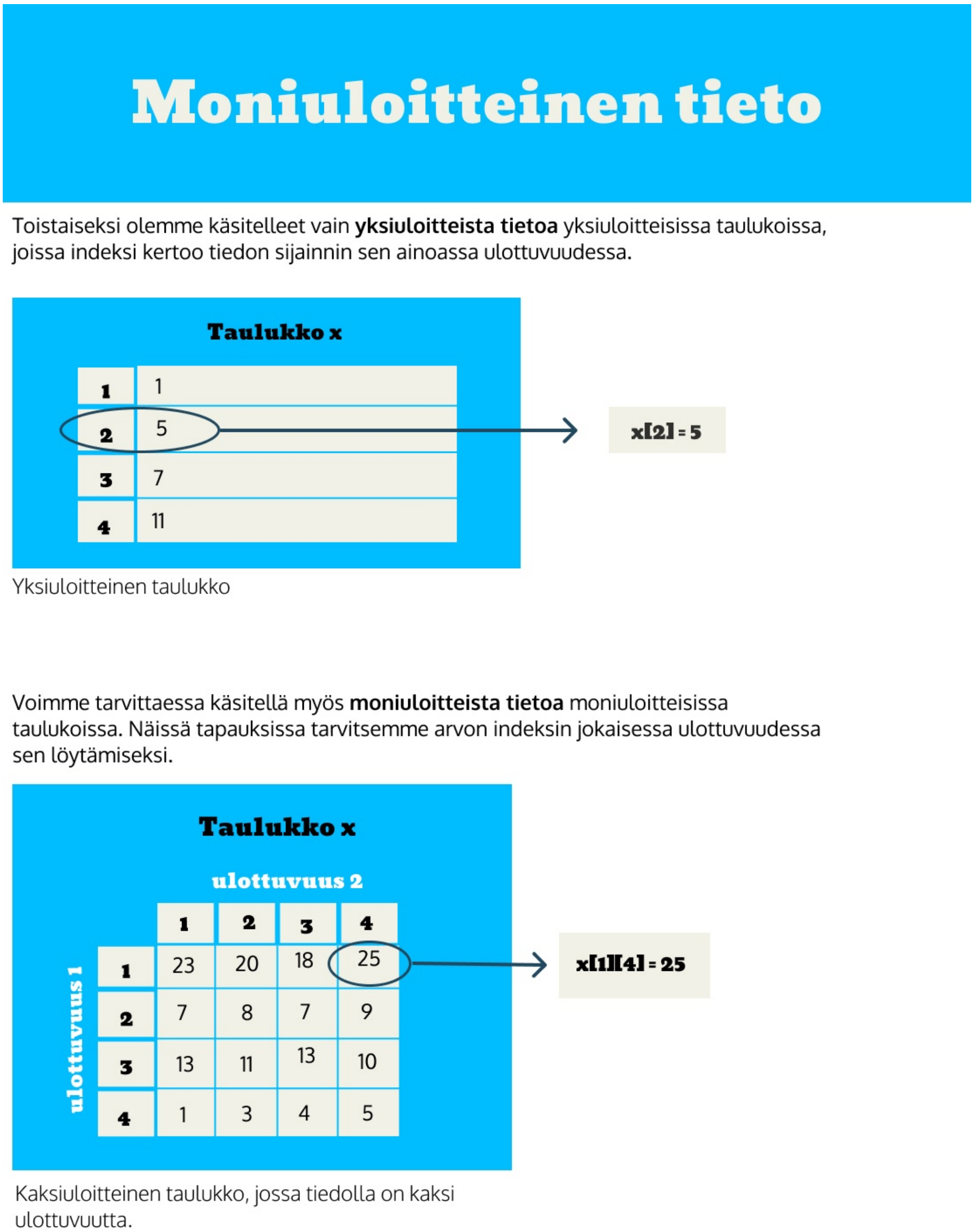


Figure 8: Viewing condition of the Multidimensional arrays experiment on low abstraction level. Displayed here in Finnish as it was presented to participants.

The responding condition with both abstraction conditions contained an interactive PowerPoint presentation embedded in the instructional material. It explained the data structure using text and images, allowed students to click back and forth to go forwards and backward in the material, and contained three questions about the data structure between topics. An image of the responding condition on the high abstraction level for the hash table test is displayed in Figure 9.

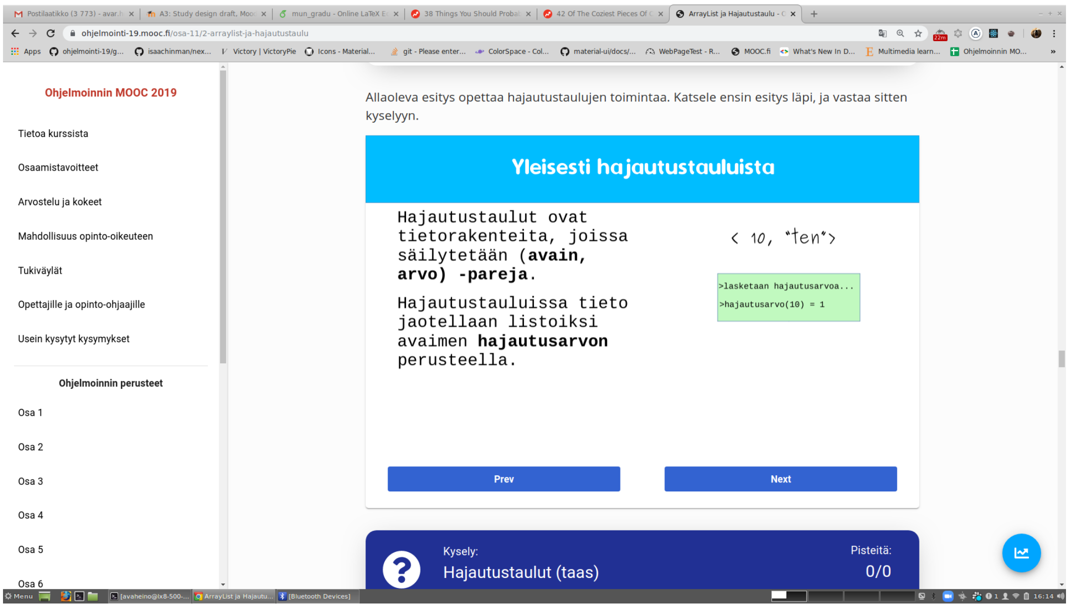


Figure 9: One view of the interactive responding condition of the hash table experiment on high abstraction level. Displayed here in Finnish as it was presented to participants.

The visual and textual representations differed between the abstraction conditions. For high abstraction level, words and images close to items familiar from everyday life were used to illustrate the concepts, such as showing lists as a regular bullet point list on a piece of paper. Some details on programmatic implementations of the data structures were also emitted in this abstraction condition. For low abstraction level, words and images closer to traditional pictorial representations of data structures were used together with pseudocode. Some details on the programmatic implementation of the data structures were also added in. The visual style was otherwise kept consistent between all visualizations. Figure 10 displays a section of high abstraction level viewing condition for the hash table experiment, and Figure 11 displays the same section for low abstraction level.

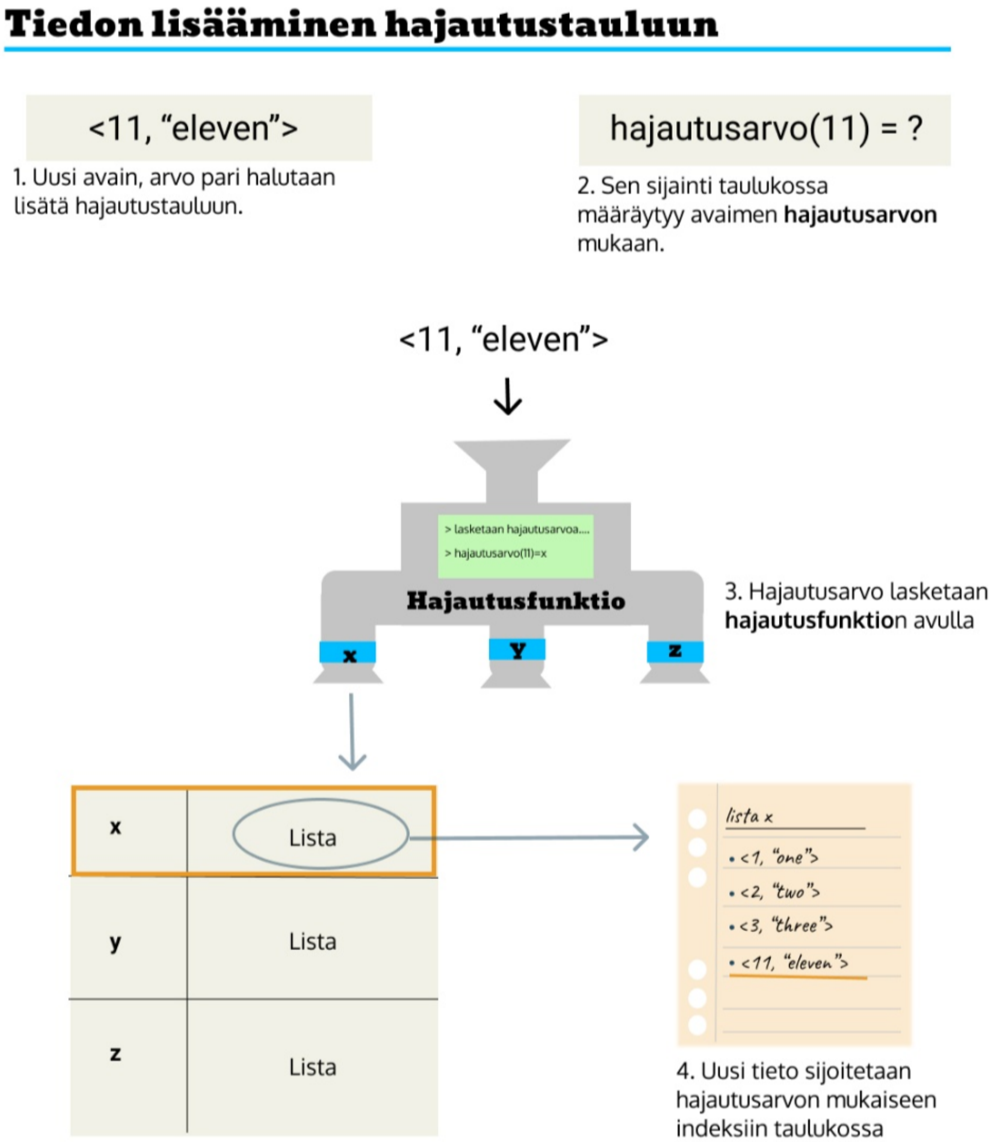


Figure 10: Section of high abstraction level - viewing condition for the hash table experiment. Displayed in Finnish as it was presented to participants.

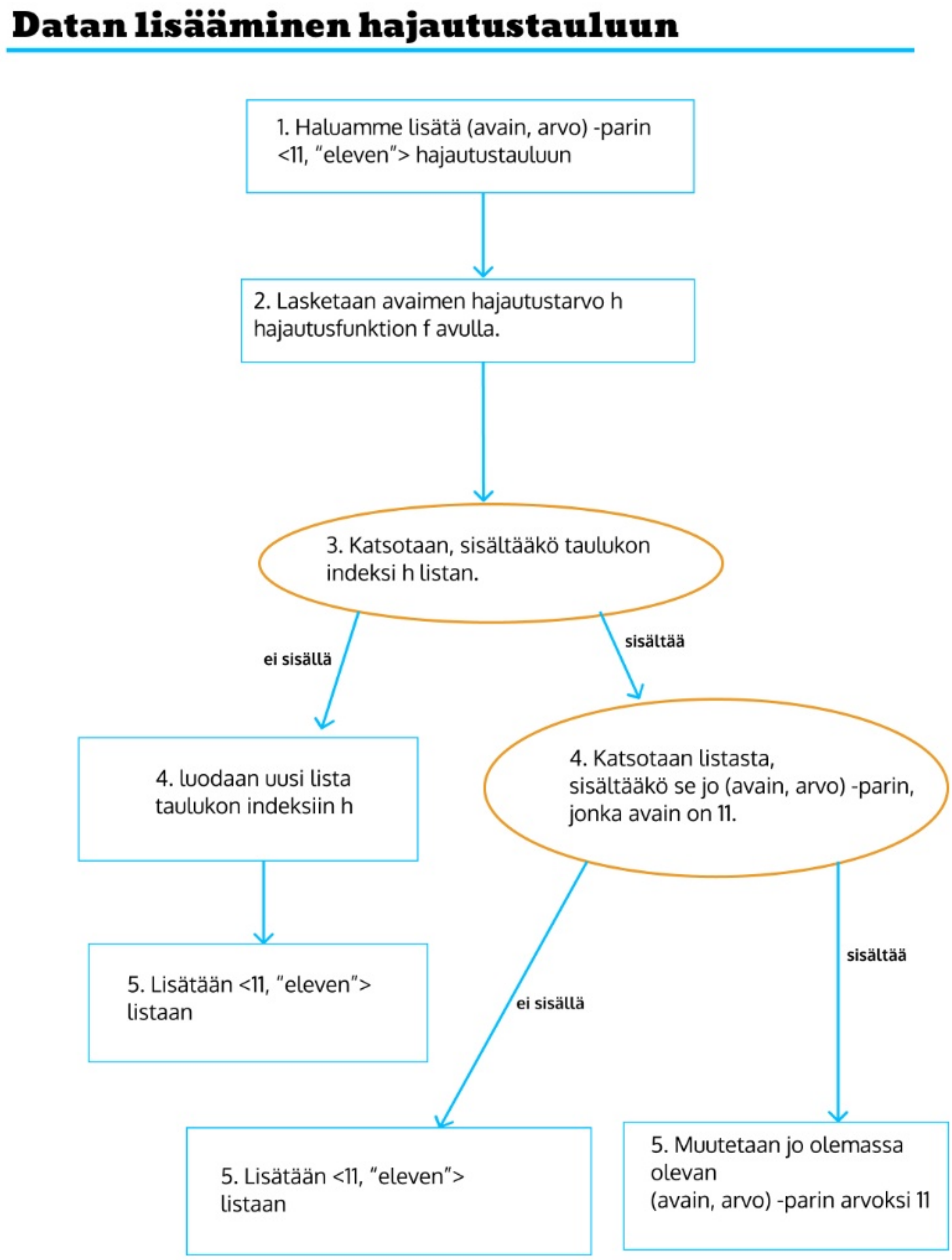


Figure 11: Section of low abstraction level - viewing condition for the hash table experiment. Displayed in Finnish as it was presented to participants.

4.2.3 Post-test

The post-test questionnaire included three parts. First, participants were asked to rate the mental effort of studying the material using the mental effort scale described in section 4.2.1, and to rate the instructional material from very easy to understand to not at all easy to understand. Then, participants were asked to answer a multiple-choice questionnaire about the topic of the visualization. The multiple-choice questionnaire contained three questions measuring participants' understanding of the topic. The questions translated to English are listed below. Questions used in the material, in Finnish, can be found from appendixes 5 and 7.

The questions for the Hash table experiment were:

1. The location of a <key, value> pair in a Hash Table is decided by?
   (a) The key
   (b) the hash value of the key
   (c) the hash value of the value
2. Why is dividing <key, value> pairs into short lists useful?
   (a) It is faster to add new pairs to a short list
   (b) It takes less storage space
   (c) It is faster to go through a short list to find a value than it would be to go through a longer list.
3. When would using a Hash table NOT be a good idea?
   (a) When the stored data needs to be stored in order
   (b) When you have too much, i.e thousands of pairs of data to store.
   (c) When you need to be able to find a value from the data structure fast.

The questions for the multidimensional arrays experiment were:

1. In Java, multidimensional arrays are?
   (a) Arrays containing arrays
   (b) Lists containing arrays
   (c) Lists containing lists

2. Which of the following is an example of two-dimensional data?
   (a) Storing the scores of one student
   (b) Storing the exam results of all students of a class
   (c) Storing the scores of students by their major
3. How is finding a value from a multidimensional array different, than finding a value from a hash tables
   (a) With multidimensional arrays, you always have to iterate over multiple arrays, whereas with hash tables you only have to iterate over a short list.
   (b) With a multidimensional array, if the indexes of the value are known, you can access the value without iterating over anything, whereas with hash tables you always have to iterate over a list of items with the same hash value.
   (c) With hash tables, if the hash value of the key of the value is known, you can access the value without iterating over anything, whereas with multidimensional arrays you have to iterate over multiple arrays to find a particular value.

Finally, participants were asked to rate the mental effort of answering the multiple-choice questionnaire using the mental effort scale described in section 4.2.1.

4.3 Procedure

On week 11 of the courses, the test questionnaires and instructional materials were embedded into the regular online instructional materials of the courses. Each participant was able to view the instructional materials for their treatment condition, and the pre- and post-test questionnaires as well as the NASA-TLX questionnaire.

Participants studied the instructional material and answered the quizzes as a part of the coursework for week 11 of the courses. The instructional materials were published online at the end of the week, as is customary for Java Programming II.

4.4 Data analysis

4.4.1 Data

In the post-test phase, we asked participants to evaluate the mental effort of both studying the instructional material and answering the post-test questionnaire using a 1-9 Likert scale. Participants also answered a 3 question multiple-choice questionnaire. Participants were awarded 1 point for each correct answer in the post-test questionnaire, making the possible scores 0-3.

In the pre-test phase, participants rated their current knowledge of the topic they would be studying from " have never heard of this topic" to "I know what this topic is and I have used the data structure in question." The scores were given numerical values 0-2. Participants also answered a 3 question multiple-choice questionnaire about the topic they would be studying. Participants were awarded 1 point for each correct answer on the questionnaire, making the possible scores 0-3. Participants were also asked to rate the mental effort of answering the pre-test questionnaire using a 1-9 Likert scale.

Participants rated the physical and mental effort of the tasks they had completed within the last hour before the testing using the NASA-TLX questionnaire. It contained six questions, each asking to rate different aspects of the tasks on 7 point scales. The questions can be found in appendix 2. All measured variables, their possible scores, and details are described in Table 6.

Measured variable	**Possible values**	**Explanation**
Prior knowledge	0-2	Self evaluation of current knowledge
Pre-test score	0-3	Number of correct answers in the pre-test questionnaire
Pre-test cognitive load	1-9	Self evaluation of pre-test mental effort
Study cognitive load	1-9	Self evaluation of study mental effort
Post-test score	0-3	Number of correct answers in the post-test questionnaire
Test cognitive load	1-9	Self evaluation of the post-test mental effort
NASA-TLX Mental Demand	0-7	Mental demand of tasks completed withing the last hour before testing
NASA-TLX Physical Demand	0-7	Physical demand of tasks completed withing the last hour before testing
NASA-TLX Temporal Demand	0-7	Temporal demand of tasks completed withing the last hour before testing
NASA-TLX Performance	0-7	Self evaluation of performance on tasks completed withing the last hour before testing
NASA-TLX Effort	0-7	Self evaluation of effort on tasks completed withing the last hour before testing
NASA-TLX Frustration	0-7	Self evaluation of frustration on tasks completed withing the last hour before testing

Table 6: Data collected from the pre-test, post-test and NASA-TLX questionnaires, their possible values and explanations.

4.4.2 Statistical analyses and answering the research questions

The research questions for this study were as follows:

RQ1 How do engagement and abstraction together affect the instructional efficiency of instructional material?

RQ2 Does prior knowledge on the topic being studied affect the instructional efficiency of instructional material?

RQ3 How does cognitive effort expended prior to studying affect the instructional efficiency of instructional material?

Instructional efficiency was calculated for each participant from their test cognitive load, study cognitive load and post-test score. We used the instructional efficiency formula introduced in section 2.2.4 to calculate the instructional efficiency.

To answer the research questions, we analyzed the statistical significance of the effects of engagement- and abstraction levels, prior knowledge, pre-test score, pre-test cognitive load, NASA-TLX answers, and experiment to instructional efficiency using linear models.

The dependent variable was instructional efficiency. The explanatory variables were abstraction level, engagement level, experiment, prior knowledge, pre-test cognitive load, pre-test score, course (lectured or online), NASA-TLX answers, and the interaction of abstraction and engagement, abstraction level and experiment and engagement level and experiment. Abstraction level and engagement level define the treatment condition of each participant. The other variables are explained in Table 6.

In the model abstraction level, engagement level and experiment were factors, and the other variables were treated as interval scale covariates. Interactions among the other explanatory variables were also examined, but they were not statistically significant and were excluded from the model. Both experiments were also analysed separately using the same linear model without experiment factor and its interactions.

The homogeneity of the variance and the normality of the distribution of the residual term was checked using scatterplots and normal probability plots. Statistical computations were done using R v3.6.2, and the Anova tests (type III) were computed using a library car.

To further analyze learning outcomes, we calculated the learning gain for each participant. It was calculated by subtracting participant's pre-test scores from their post-test scores to measure how many points their score increased after studying. The effect of treatment condition on learning gain was analyzed using a linear model with learning gain as the dependent variable and treatment condition as the explanatory variable. Treatment condition was a factor.

Results will be discussed in detail in section 5, where we will report the p-values of the effects of the different variables. We will also report the effect sizes where applicable.

5 Results

In this section, we detail the results of our study. First, we provide an overview of the data and the significance of the effects of the different variables. Then we detail the results of both experiments together, and the results of the hash table experiment and the multidimensional arrays experiment separately.

5.1 Overview

We tested altogether 123 participants in two experiments: The hash table experiment and the multidimensional arrays experiment. As most participants took part in both experiments, 121 participants completed the hash table experiment, and 114 participants completed the multidimensional arrays experiment.

Table 7 describes the mean values of pre-test score, pre-test knowledge (self-reported), pre-test cognitive load, test result, study cognitive load,test cognitive load and learning gain (the difference between pre-test score and test result) for both experiments as well as for the whole data set. Table 8 describes the mean test result, study cognitive load, and test cognitive load for both experiments as well as for the whole data set by treatment condition.

Measurement	Whole data set	Hash table experiment	Multidimensional arrays experiment
Pre-test score	0.38	0.31	0.45
Pre-test knowledge	1.39	1.96	0.78
Pre-test cognitive load	2.98	3.21	2.73
Test result	0.81	0.90	0.73
Study cognitive load	3.30	3.63	2.96
Test cognitive load	2.99	2.77	3.23
Learning gain	0.44	0.60	0.28

Table 7: Mean values of measured variables in the whole data set, hash table experiment and multidimensional arrays experiment.

Test result			
Treatment condition	Whole data set	HT	MD
1	0.84	0.96	0.71
2	0.84	1	0.64
3	0.82	0.85	0.80
4	0.80	0.87	0.71
5	0.79	0.90	0.71
6	0.82	0.90	0.74
Test cognitive load			
1	2.71	2.19	3.27
2	3.07	2.53	3.75
3	2.98	3.04	2.91
4	3.14	3.03	3.29
5	3.14	2.94	3.29
6	2.86	2.55	3.14
Study cognitive load			
1	3	2.94	3.07
2	3.30	3.20	3.42
3	3.23	3.38	3.09
4	3.47	4.00	2.71
5	3.27	3.94	2.76
6	3.43	4.00	2.91

Table 8: Mean values of study cognitive load, test cognitive load and test result for the whole data set, hash table experiment (HT) and the multidimensional arrays experiment (MD) by treatment condition.

Instructional efficiency was calculated for each participant using their test result, study cognitive load, and test cognitive load. Instructional efficiency varied between -6.02 and 1.92 for the whole data set, -6.78 and 1.83 for the hash table experiment and -4.38 and 2.09 for the multidimensional arrays experiment. The mean instructional efficiency was 0 for both tests.

The significance of the effects of the different variables on instructional efficiency for the whole data set are described in Table 9:

Effect	p value
Engagement level	0.27
Abstraction level	0.03
Experiment	0.01
Pre-test score	0.03
Prior knowledge	0.83
Pre-test cognitive load	< 0.01
Course	0.09
NASA-TLX Mental demand	0.61
NASA-TLX physical exertion	0.02
NASA-TLX Temporal demand	0.54
NASA-TLX Performance	0.23
NASA-TLX Effort	0.17
NASA-TLX Frustration	0.19
Interaction of abstraction and engagement	0.62
Interaction of engagement and experiment	0.01
Interaction of abstraction and experiment	0.03
Interaction of abstraction, engagement and experiment	0.24

Table 9: Significance of effects of different variables

The significance of the effects of the different variables for the hash table experiment are described in Table 10:

Effect	p value
Engagement level	0.25
Abstraction level	0.03
Pre-test score	0.18
Prior knowledge	0.71
Pre-test cognitive load	< 0.01
Course	0.11
NASA-TLX Mental demand	0.73
NASA-TLX physical exertion	0.28
NASA-TLX Temporal demand	0.54
NASA-TLX Performance	0.49
NASA-TLX Effort	0.90
NASA-TLX Frustration	0.20
Interaction of abstraction and engagement	0.66

Table 10: Significance of effects of different variables for the hash table experiment

The significance of the effects of the different variables for the multidimensional arrays experiment are described in Table 11:

Effect	p value
Engagement level	0.06
Abstraction level	0.59
Pre-test score	0.17
Prior knowledge	0.71
Pre-test cognitive load	< 0.01
Course	0.57
NASA-TLX Mental demand	0.33
NASA-TLX physical exertion	0.05
NASA-TLX Temporal demand	0.96
NASA-TLX Performance	0.40
NASA-TLX Effort	0.16
NASA-TLX Frustration	0.81
Interaction of abstraction and engagement	0.46

Table 11: Significance of effects of different variables for the multidimensional arrays experiment

5.2 Combined results

In this section, we will address the results of both the hash table experiment and the multidimensional arrays experiment together. The results of both experiments will be discussed separately in the following sections.

5.2.1 Engagement and abstraction

The effects of engagement level or the interaction of engagement level and abstraction on instructional efficiency were not statistically significant. Abstraction level had a significant effect (p=0.03).

The variances of distributions of instructional efficiency by abstraction level are described in Figure 12.

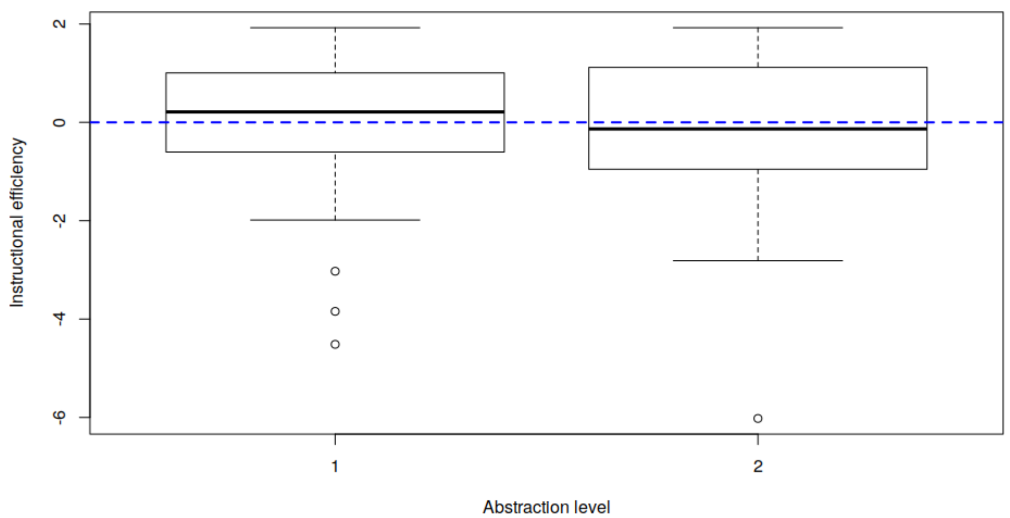


Figure 12: Instructional efficiency by abstraction level. 1 = high abstraction, 2 = low abstraction.

Instructional efficiency was calculated from test result, study cognitive load and test cognitive load. Table 8 describes their mean values by treatment condition. Figure 13 describes the variances of distributions of instructional efficiency by treatment condition.

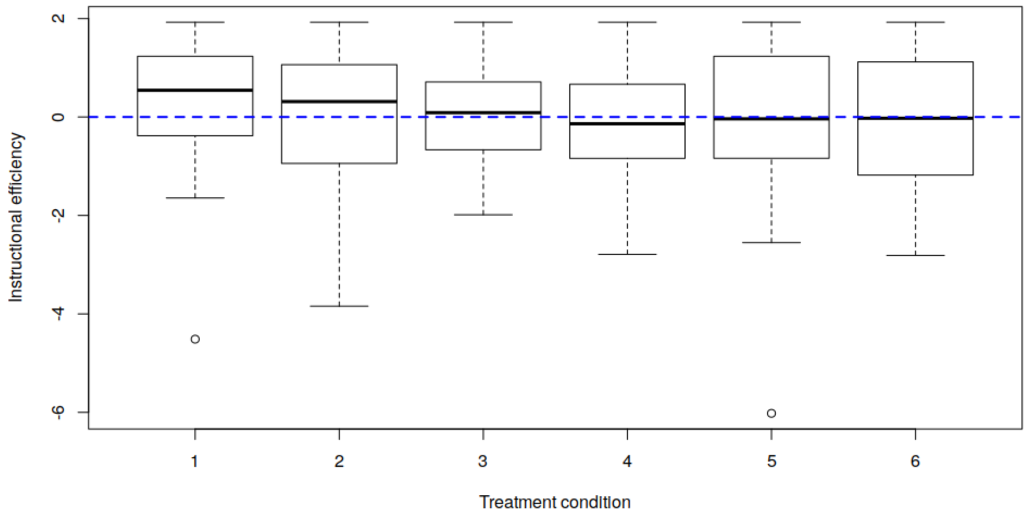


Figure 13: Instructional efficiency by treatment condition. 1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction - no viewing, viewing, responding.

Learning gain refers to the difference between participant's pre-test score and their test result. Treatment condition did not have a significant effect to learning gain (p=0.16). The variances of the distributions of learning gain by abstraction level are described in Figure 14.

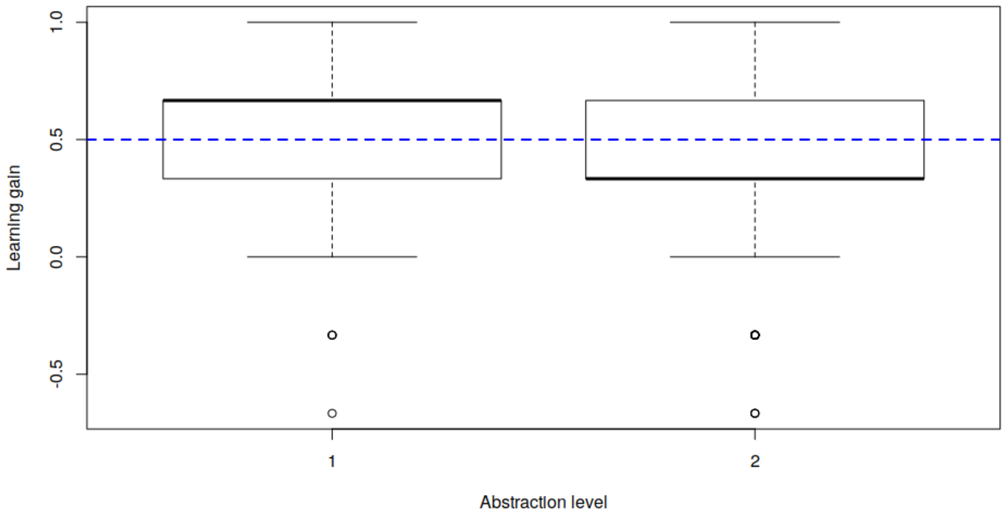


Figure 14: Learning gain by abstraction level. 1 = high abstraction, 2 = low abstraction.

The variances of the distributions of learning gain by treatment condition are described in Figure 15.

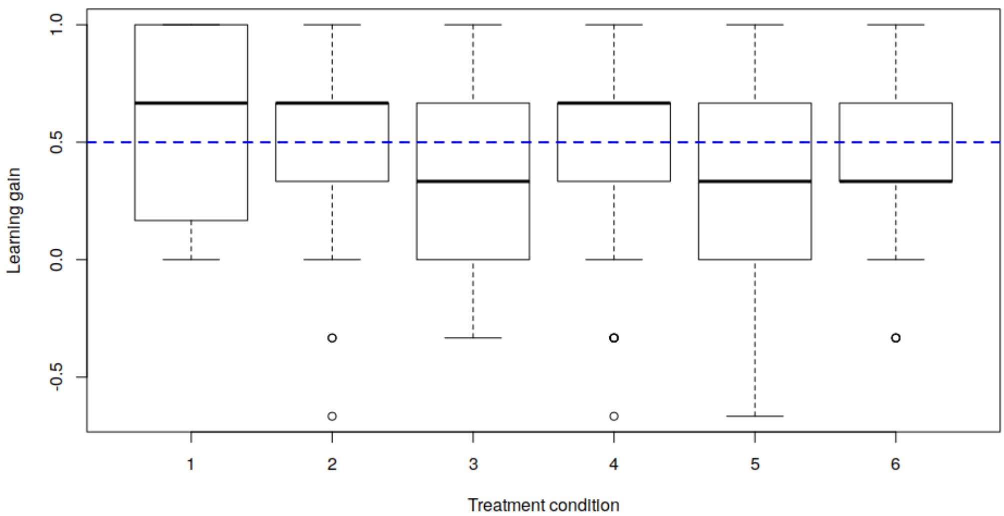


Figure 15: Learning gain by treatment condition. 1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction - no viewing, viewing, responding.

5.2.2 Prior knowledge

We used three different measures of prior knowledge: self-evaluated prior knowledge, pre-test score, and experiment.

In the pre-test questionnaire, participants rated their knowledge of the topic they would be studying (either hash tables or multidimensional arrays) from 0 to 2. Participants also answered a multiple-choice questionnaire about the topic. The instructional materials themselves were also different - participants had studied an introductory chapter to hash tables previously on the course giving all participants some prior knowledge on the topic, but the students had not studied multidimensional arrays on the course yet, so it was a new topic to majority of the participants.

Participants' own evaluation of their knowledge had no significant effect on instructional efficiency. Their pre-test score, the number of correct answers in the pre-test questionnaire, had a positive effect (regression coefficient b=0.56, p=0.03). Figure 16 describes the variances of distributions of instructional efficiency by pre-test score.

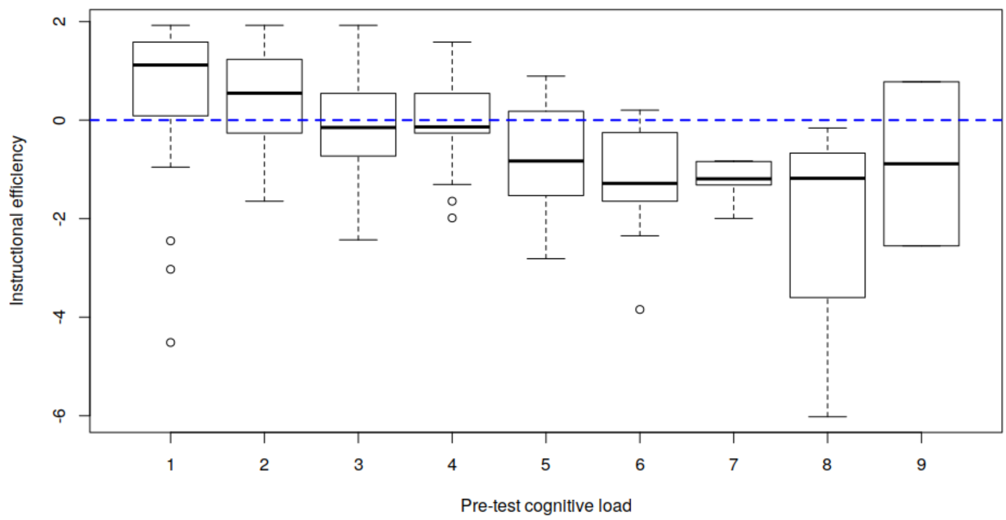


Figure 16: Instructional efficiency by pretest score

Table 12 describes the mean study cognitive load, test cognitive load and test result by pre-test score.

Score	Test result	Study cognitive load	Test cognitive load
0	0.78	3.68	3.07
1	0.87	3.5	3.06
2	0.80	2.92	2.87
3	0.78	2.50	2.79

Table 12: Test result,study cognitive load and test cognitive load means by pre-test score

Pre-test score did not have any significant interaction effect with the treatment condition. This suggests that although higher pre-test score tends to lead to higher instructional efficiency, the effect is the same across the treatment conditions and no treatment condition works better for participants with high pre-test score.

Interaction effects of engagement level and experiment and abstraction level and experiment were statistically significant (p=0.01 for engagement level and p=0.03 for abstraction level). The interaction effect of engagement level, abstraction level, and experiment was not statistically significant (p=0.24).

Figure 17 describes the variances of distributions of instructional efficiency by treatment condition for both experiments.

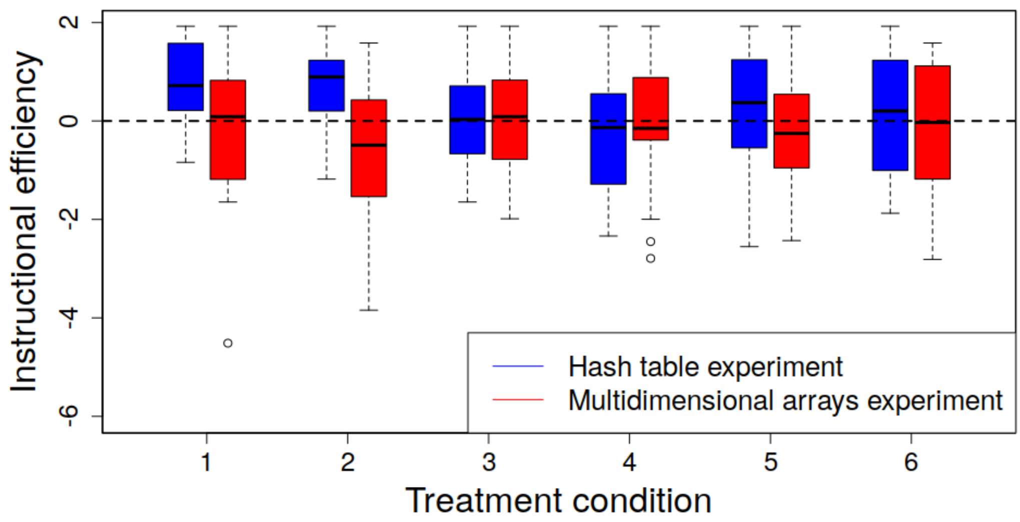


Figure 17: Instructional efficiency by treatment condition for both tests.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction - no viewing, viewing, responding.

As can be seen from Figure 17, on high abstraction levels (treatment groups 1,2, and 3), participants of the hash table experiment achieved higher instructional efficiency on the no viewing condition, and the instructional efficiency decreased when the engagement level was increased. Participants of the multidimensional arrays experiment had the opposite results, responding condition leading to the highest instructional efficiency and efficiency decreasing with decreasing engagement levels.

5.2.3 Prior cognitive load

Participants' cognitive load prior to the study was measured using the NASA-TLX questionnaire asking participants to rate the mental and physical effort they have expended within the last hour. Physical exertion reported in the NASA-TLX did have a positive effect (regression coefficient b=0.12,p=0.02) on instructional efficiency. The variances of the distributions of instructional efficiency by NASA-TLX physical exertion score is described on Figure 18.

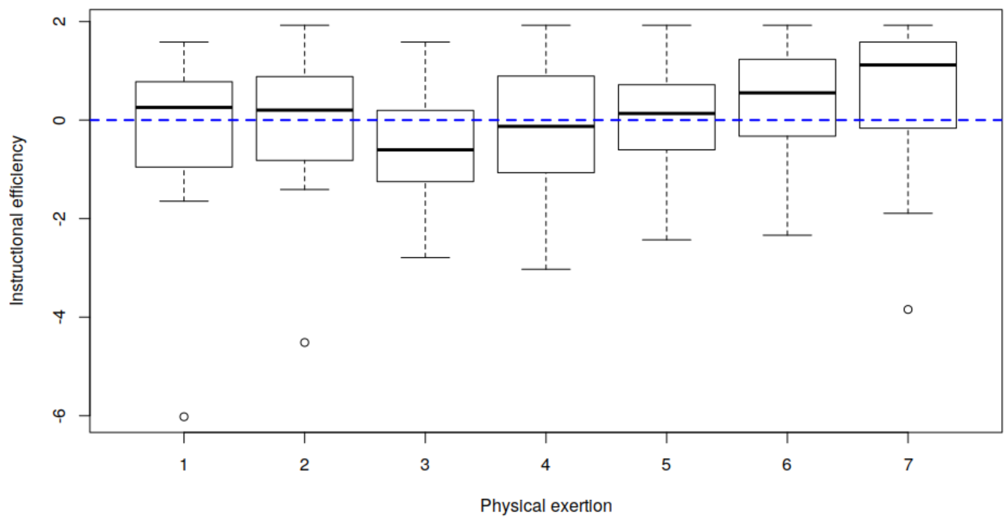


Figure 18: Instructional efficiency by NASA-TLX physical exertion score

Figures 19 and 20 describe test cognitive load and study cognitive load by NASA-TLX physical exertion score

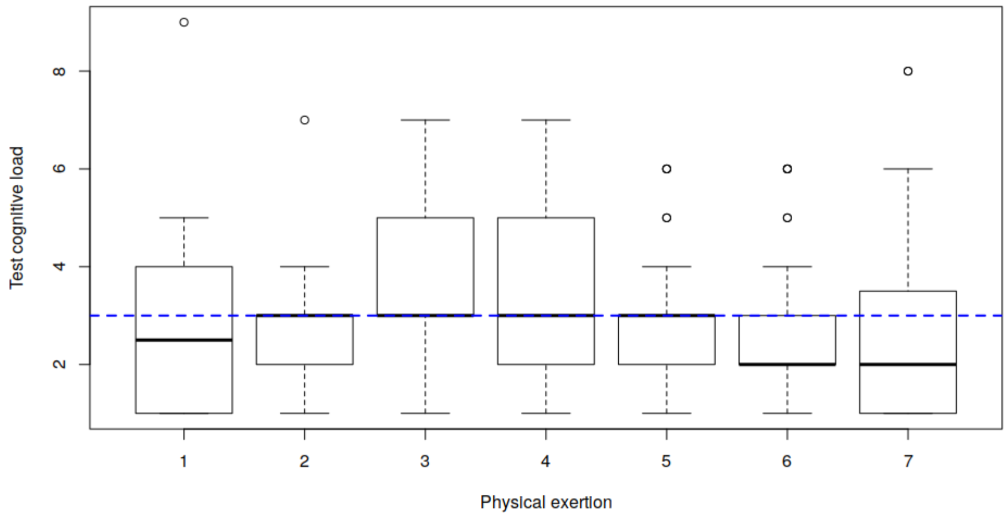


Figure 19: Test cognitive load by NASA-TLX physical exertion score

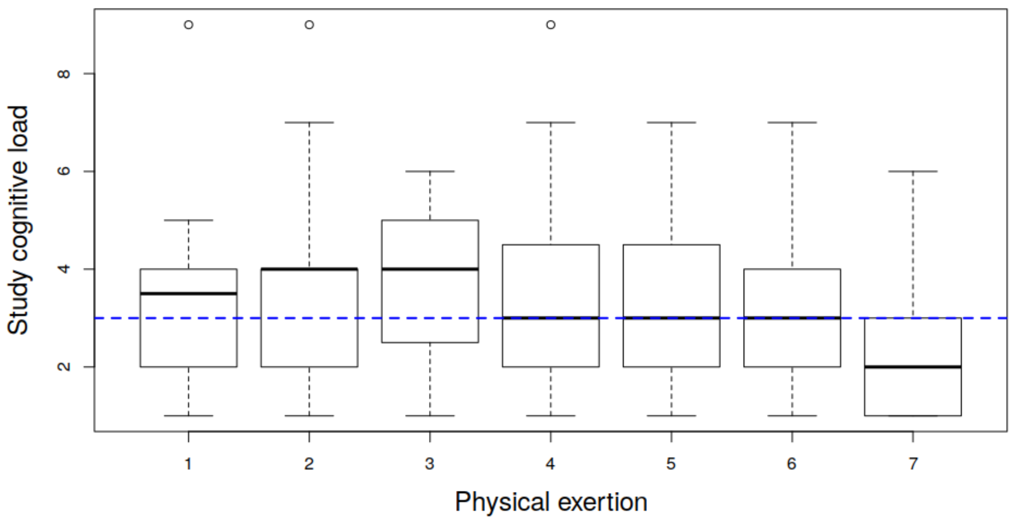


Figure 20: Study cognitive load by NASA-TLX physical exertion score

Participants' pre-test cognitive load was measured in the pre-test phase by asking them to rate the mental effort of answering the pre-test questionnaire 1-9 1 being no effort at all, 9 being high mental effort.

Pre-test cognitive load had a significant negative effect on instructional efficiency (regression coefficient b=-0.37, $p < 0.01$). Pre-test cognitive load and treatment condition did not have any significant interaction effect, suggesting that high prior cognitive load lessens the instructional efficiency of all of the materials. No treatment condition performed better for participants with high pre-test cognitive load. Figure 21 describes the variances of the distributions of the instructional efficiency by pre-test cognitive load.

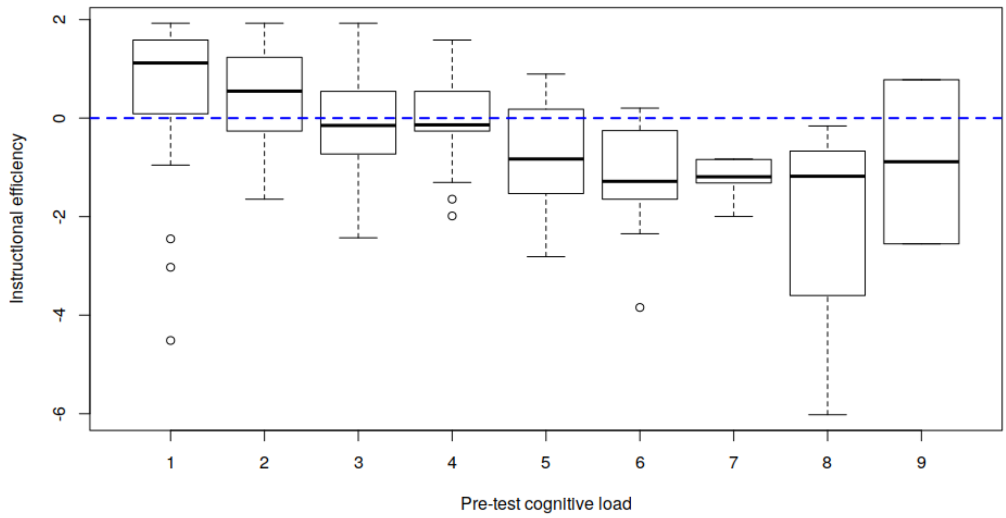


Figure 21: Instructional efficiency by pretest cognitive load

5.3 Hash table experiment

This section will discuss the analysis of the hash table experiment.

5.3.1 Engagement and abstraction

The effect of abstraction level on instructional efficiency was significant in this experiment (p=0.03). The effects of engagement level or interaction of engagement level and abstraction level on instructional efficiency were not significant (p=0.25 for engagement level and p=0.66 for interaction of engagement level and abstraction level). Table 13 describes the mean instructional efficiency by treatment condition for the hash table experiment. Figure 22 describes the variances of the instructional efficiency distributions by treatment condition.

Treatment condition	Instructional efficiency
1	0.75
2	0.64
3	0.03
4	-0.13
5	-0.01
6	0.12

Table 13: Instructional efficiency by treatment condition for the hash table experiment

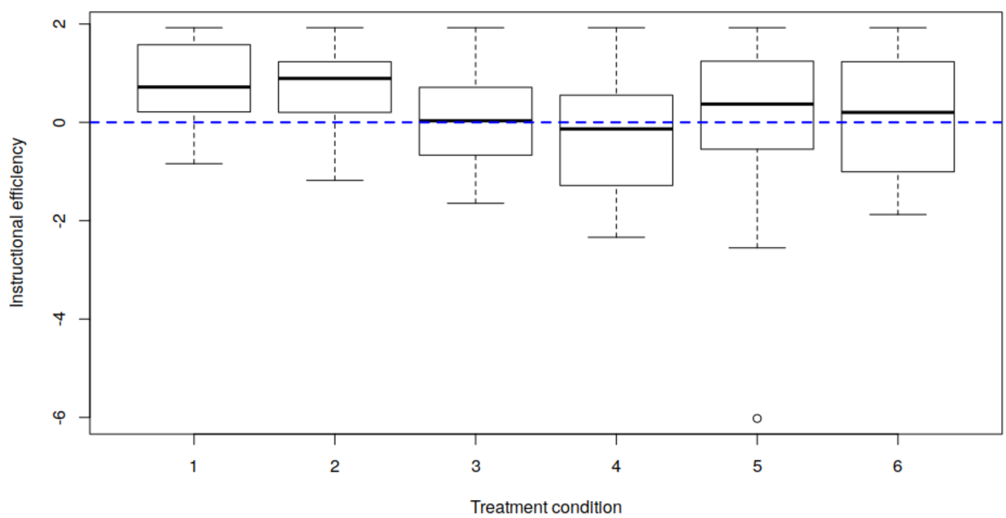


Figure 22: Instructional efficiency by treatment condition for hash table experiment.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction - no viewing, viewing, responding.

There were no significant differences between the test results from different treatment conditions in the hash table experiment. Figures 23 and 24 describe the variances of the distributions of study cognitive load and test cognitive load by treatment condition for the hash table experiment.

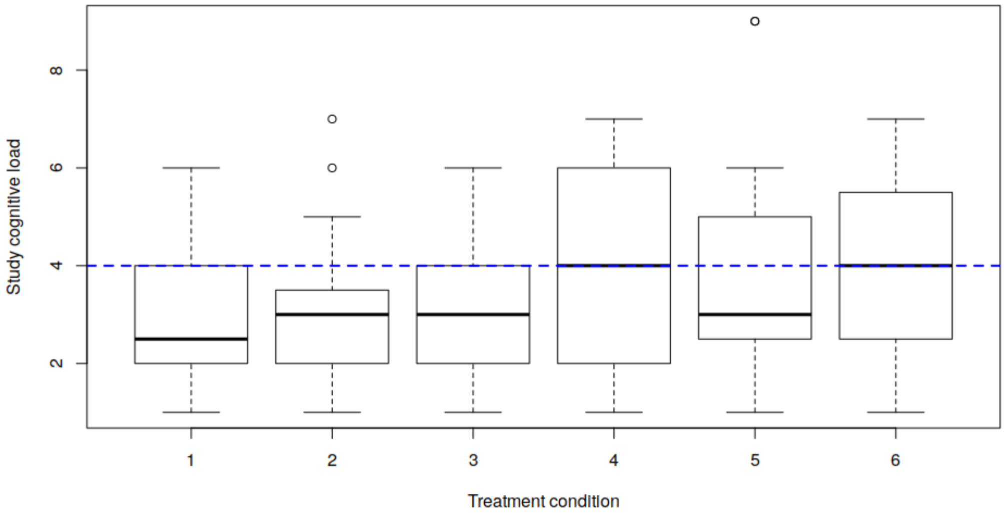


Figure 23: Study cognitive load by treatment condition for hash table experiment.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction - no viewing, viewing, responding.

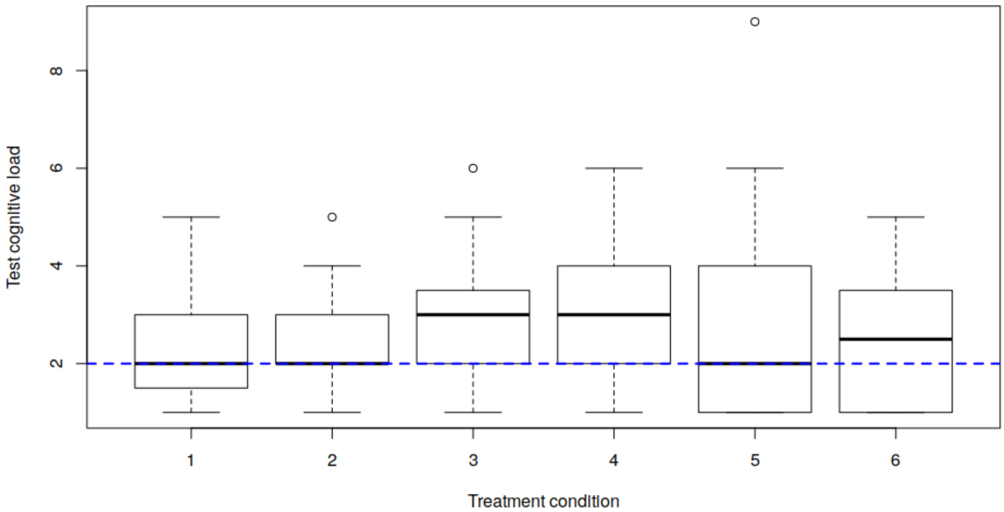


Figure 24: Test cognitive load by treatment condition for hash table experiment.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction - no viewing, viewing, responding.

Treatment condition had a small effect to learning gain in the hash table experiment (p=0.07). The variances of learning gain distributions by treatment condition for the hash table experiment is described in Figure 25

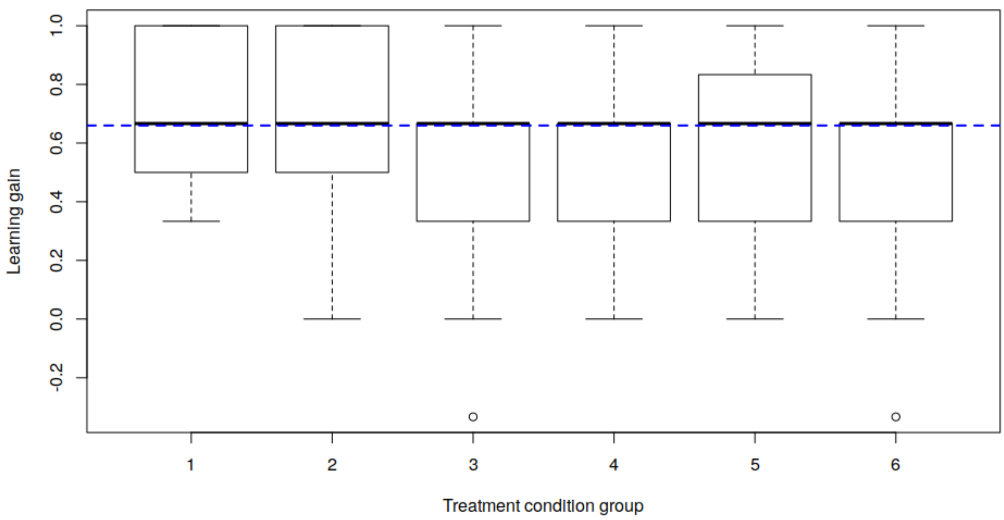


Figure 25: Learning gain by treatment condition for the hash table experiment.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction, no viewing, viewing, responding.

5.3.2 Prior knowledge

In this experiment, the effects of neither pre-test score (regression coefficient b=0.53,p=0.18) nor self-reported prior knowledge (regression coefficient b = -0.18 p=0.71) on instructional efficiency were not statistically significant. Participants in this experiment had studied an introductory chapter to hash tables previously in the course. From 121 participants in this test, 116 evaluated their prior knowledge as 2, only 5 evaluated their prior knowledge as 1, and no participant evaluated their prior knowledge as 0.

Figure 26 displays the variances of instructional efficiency distributions by pre-test score for the hash-table experiment.

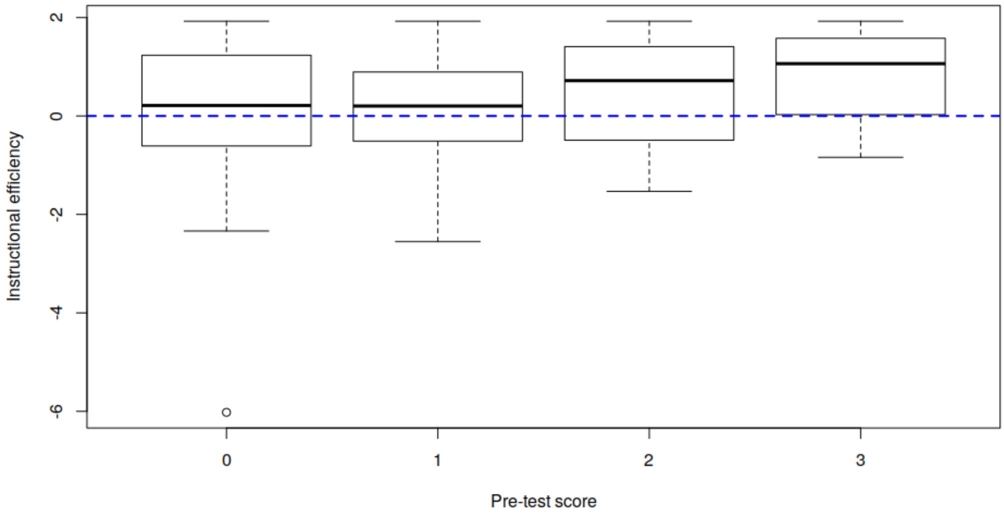


Figure 26: Instructional efficiency by pre-test score for hash table experiment

Table 14 describes mean test result, study cognitive load and test cognitive load by pre-test score for the hash table experiment.

Score	Test result	Study cognitive load	Test cognitive load
0	0.86	3.97	2.6
1	0.92	3.77	2.95
2	0.88	2.75	2.55
3	1	2.75	2.50

Table 14: Test result,study cognitive load and test cognitive load means by pre-test score for the hash table experiment

5.3.3 Prior cognitive load

Looking at the hash table experiment alone, The effects of the results of the NASA-TLX questionnaire were not significant.

The effect of the pre-test cognitive load on instructional efficiency was significant (regression coefficient $b=-0.4, p<0.01$). Figure 27 describes the variances of the instructional efficiency distributions by pre-test cognitive load for the hash table experiment.

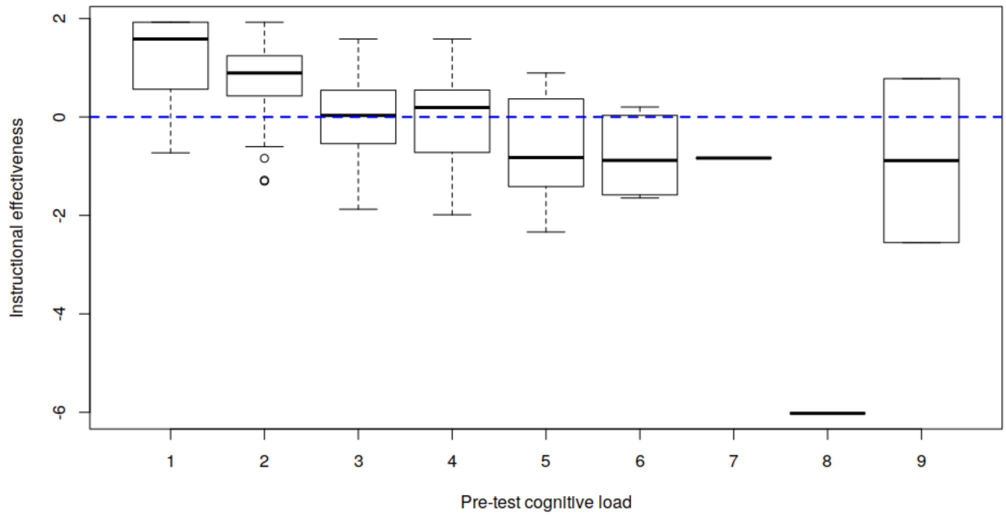


Figure 27: Instructional efficiency by pre-test cognitive load for hash table experiment

5.4 Multidimensional arrays experiment

This section will discuss the analysis of the multidimensional arrays experiment.

5.4.1 Engagement and abstraction

In the multidimensional arrays experiment, the effect of the engagement level on instructional efficiency was statistically significant (p=0.06). The effects of the abstraction level or the interaction between engagement level and abstraction level were not statistically significant (p=0.59 for the abstraction level and p=0.46 for the interaction between the engagement level and the abstraction level). Figure 28 describes the variances of instructional efficiency distributions by treatment condition.

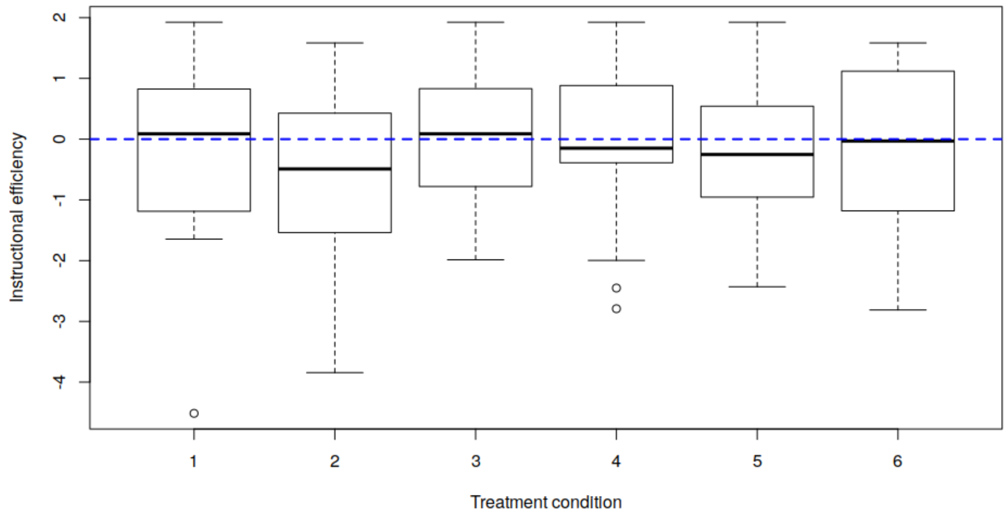


Figure 28: Instructional efficiency by treatment condition for multidimensional arrays experiment.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction, no viewing, viewing, responding.

Table 15 describes mean instructional efficiency by treatment condition for the multidimensional arrays experiment.

Treatment condition	Instructional efficiency
1	-0.27
2	-0.74
3	0.05
4	-0.15
5	-0.17
6	-0.10

Table 15: Instructional efficiency means by treatment condition for the multidimensional arrays experiment.1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction, no viewing, viewing, responding.

Treatment condition did not have an effect to learning gain in the multidimensional arrays experiment ($p=0.83$). The variances of the learning gain distributions by treatment condition group for the hash table experiment are described in Figure 29.

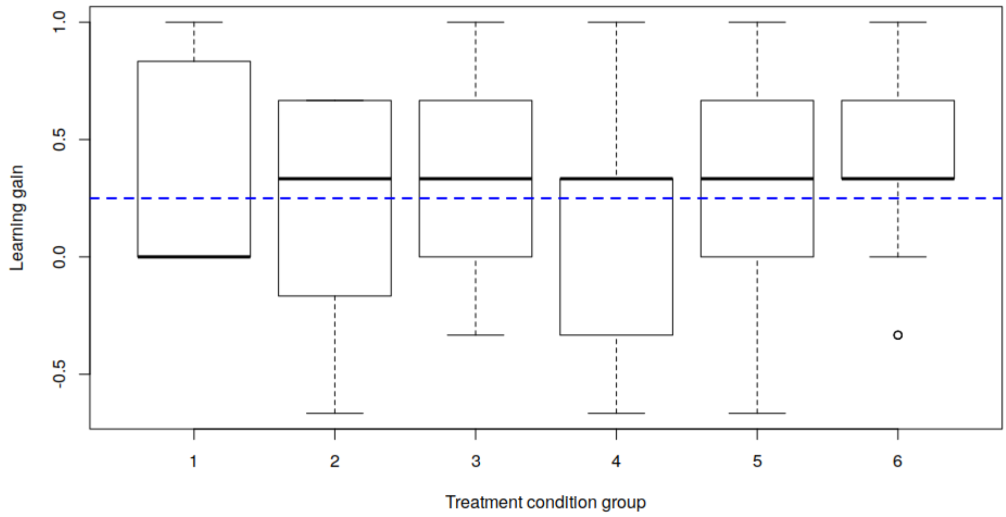


Figure 29: Learning gain by treatment condition for the multidimensional arrays experiment. 1-3 = high abstraction - no viewing, viewing, responding. 4-6 = low abstraction, no viewing, viewing, responding.

5.4.2 Prior knowledge

In the multidimensional arrays experiment, the effect of self-evaluated prior knowledge on instructional efficiency was not statistically significant (p=0.71). From the 114 participants who completed the multidimensional arrays experiment, 43 evaluated their prior knowledge as 0, 53 evaluated their prior knowledge as 1, and 18 evaluated their prior knowledge as 2.

The effect of the pre-test score on instructional efficiency was not statistically significant either (p=0.17). Figure 30 describes the variances of the instructional efficiency distributions by pre-test score.

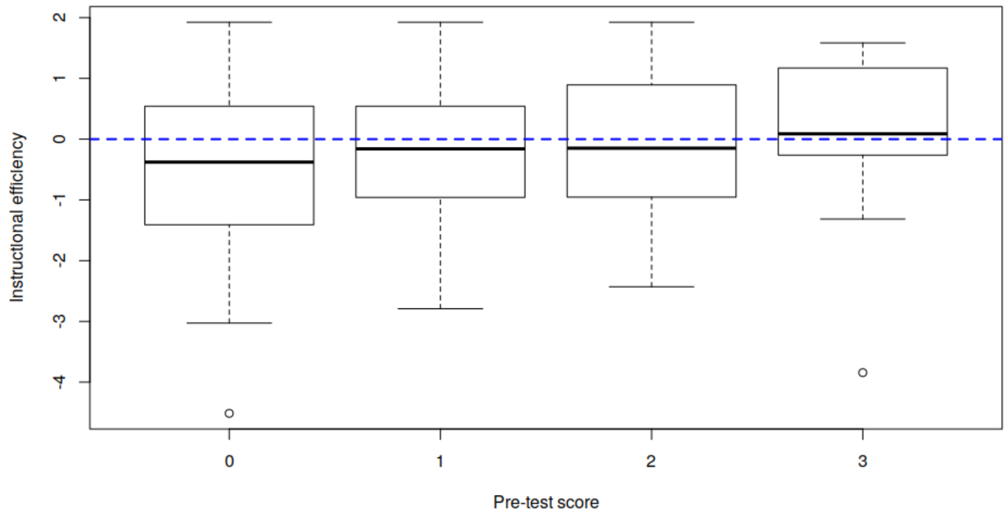


Figure 30: Instructional efficiency by pre-test score for multidimensional arrays experiment.

Table 16 describes mean test results, study cognitive load and test cognitive load by pre-test score for the multidimensional arrays experiment.

Score	Test result	Study cognitive load	Test cognitive load
0	0.70	3.24	3.58
1	0.73	2.89	3.30
2	0.75	3.02	3.06
3	0.73	2.45	2.85

Table 16: Test result,study cognitive load and test cognitive load means by pre-test score for the multidimensional arrays experiment

5.4.3 Prior cognitive load

In the multidimensional arrays experiment the effect of physical exertion reported in the NASA-TLX questionnaire on instructional efficiency was significant (regression coefficient b=0.16,p=0.08). Figure 31 describes the variances of the instructional efficiency distributions by reported physical exertion for the multidimensional arrays experiment. In the multidimensional arrays experiment the effect of pre-test cognitive load on instructional efficiency was significant ($b=-0.35, p < 0.01$).

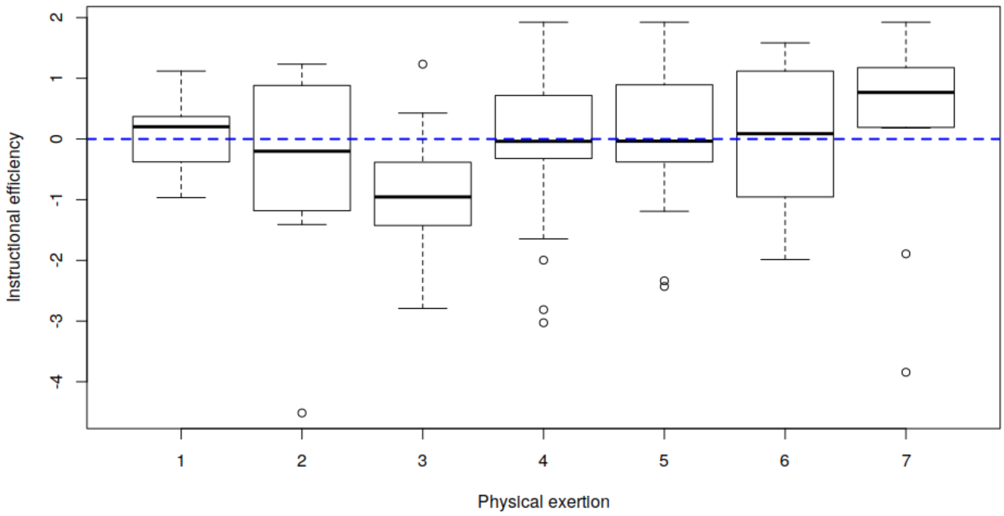


Figure 31: Instructional efficiency by physical exertion for multidimensional arrays experiment

Figure 32 describes the variances of the instructional efficiency distributions by pre-test cognitive load.

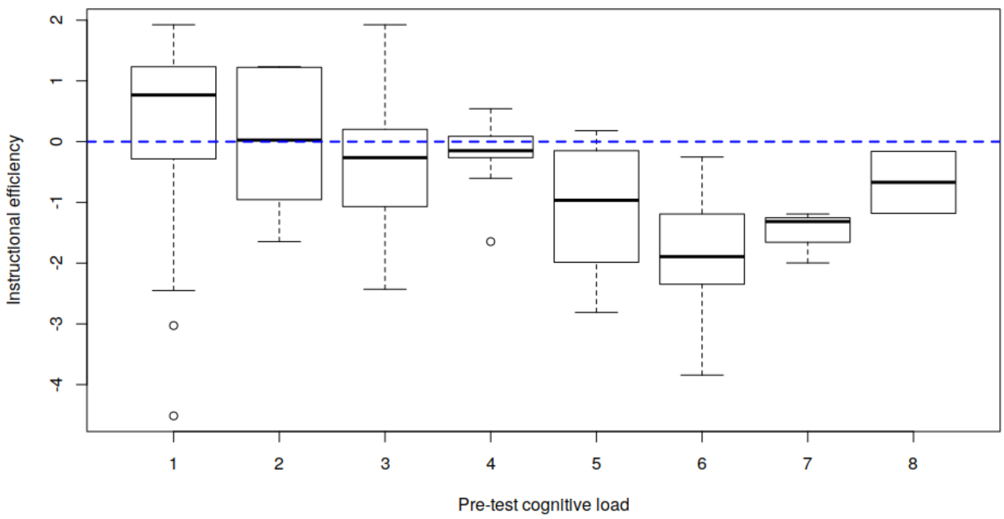


Figure 32: Instructional efficiency by pre-test cognitive load for multidimensional arrays experiment

6 Discussion

By studying the compound effect of abstraction and engagement in the instructional efficiency of an online instructional material containing visualizations in the context of a university programming course, we aimed to get insights into effects of different ways of presenting information to this kind of student population and thus develop our understanding of how these different ways of presenting information work in a real-life context.

6.1 Effect of engagement and abstraction

First, concerning the compound effect of engagement and abstraction, we expected that higher engagement would lead to better learning outcomes, evidenced by lower test cognitive load and higher test results, for both abstraction levels. Although to our best knowledge, instructional efficiency, engagement, and abstraction have not been previously studied together, studies on visualizations and cognitive load have been conducted. Schwamborn et al. studied learning outcomes and cognitive load comparing no visualizations, self-generated visualizations, and provided visualizations. They concluded that the presence of provided visualizations did increase comprehension but also increased cognitive load [STOL11]. Herrlinger et al. had similar results when evaluating learning outcomes from instructional material containing static images to learning outcomes from a material containing no images [HHOL17]. Hoffler compared static visualizations to interactive visualizations, concluding that interactive visualizations performed better than static ones in regards to learning outcome measures [HL07].

We were not able to replicate these results conclusively. In regards to the compound effect of engagement and abstraction, our hypothesis was proved mainly wrong. We could not measure any statistically significant differences between the treatment condition groups when looking at the whole data set and both factors. This indicates that although certain treatment condition groups performed better for specific subcategories of participants, no combination of engagement and abstraction seems to work better or worse universally for all participants.

We further expected higher abstraction to lead to lower study cognitive load for all engagement levels, leading to higher instructional efficiency for treatment condition groups 1,2, and 3. Our data partially supports this hypothesis. Looking at the whole data set, we measured statistically significant differences between the abstraction levels. We also measured higher study cognitive loads on the lower abstraction level. However, the effect of abstraction was not significant when analyzing the data from the multidimensional arrays experiment separately. This suggests that although lower abstraction tends to lead to higher study cognitive load and worse instructional efficiency, this effect cannot be generalized to all students.

6.2 Effect of prior knowledge on instructional efficiency

In regards to the effect of prior knowledge on instructional efficiency, we expected the high abstraction treatment conditions to outperform the low abstraction ones for participants with little or no prior knowledge on the topic of the test material. We expected that as participants with low or no knowledge on the topic of the test material have no developed schemata on the topic, the instructional material designed to limit intrinsic cognitive load and link the topic to concepts participants are familiar with from the real world would limit the cognitive load from studying the material and allow for better processing of the information.

The effect of prior knowledge on learning outcomes from different instructional material has been previously studied. Kalyuga et al. compared learning from visualizations alone and visualizations with auditory and textual explanations by inexperienced and experienced students [KCS00]. Their results indicate that multimodal material supports the learning of novices, but hinders the learning of more experienced students.

When prior knowledge was measured by the participant's score on the pre-test questionnaire, we could not repeat these results. We did not see any differences between the treatment condition groups for participants with different levels of knowledge. A high score on the pre-test questionnaire lead to better instructional efficiency overall, leading to higher test results and lower study- and test cognitive load. However, there were no differences between the treatment condition groups. Our results indicate that the level of prior knowledge does affect the instructional efficiency of instructional material. However, there does not seem to be a type of material that performs better or worse for participants with low or high prior knowledge when prior knowledge is measured as a high test score.

We did see differences between the treatment conditions between the two different experiments. One experiment was done on a topic the participants had been introduced to previously on the course, and one experiment was done on an entirely new topic. Between the two experiments the main difference was not in pre-test scores (percentage of right answers in the pre-test questionnaire), as participants in the multidimensional arrays experiment had overall higher pre-test scores than participants in the hash table experiment (0.45 vs. 0.31), but in self-evaluation of prior knowledge. Participants in the hash table experiment rated their knowledge on the topic significantly higher than participants in the multidimensional arrays experiment (1.96 vs. 0.78).

When we look at the data of the different experiments, the major difference being the self-evaluated prior knowledge, our results partially align with the results of Kalyuga et al.

For the hash table experiment, we measured significant differences between the abstraction levels. However, we can also see a downward trend in instructional efficiency between the engagement levels on the high abstraction level, although it is not statistically significant. High abstraction level no viewing condition outperformed all other conditions, and within the high abstraction level, higher engagement levels lead to a decrease in instructional efficiency. Overall we measured lower study cognitive load on the high abstraction level than on the low abstraction level. On the low abstraction level, there were no statistically significant differences between the treatment conditions, but the interactive visualization slightly outperformed the other conditions.

For the multidimensional arrays experiment, we did not measure statistically significant differences between the treatment conditions, but there were significant differences between the engagement levels. For both abstraction levels, the viewing condition performed worse than the no viewing or responding conditions, and the responding condition performed the best. For the multidimensional arrays experiment, we measured lower study cognitive load on the low abstraction level than on the high abstraction level.

The high performance of high abstraction level no viewing group in the hash table experiment can be explained by the expertise reversal effect [KCS00]. The highly abstract material is easily understandable for participants with some prior knowledge, so visual or interactive elements are redundant and hinder the learning.

Overall, the results between the experiments indicate that for participants with higher self-reported prior knowledge achieve higher instructional efficiency with the highly abstract material in a text format. Participants with low self-reported prior knowledge achieve higher instructional efficiency on less abstract material in a responsive format.

Further research is needed to assess the cause of these differences. Some of the differences could be explained by studying being easier when you already know some of the material, thus leading to higher instructional efficiency for participants of the hash table experiment. Further research is also needed to assess the differences in the knowledge levels of the two groups. The pre-test scores of the participants who reported high prior knowledge were not higher than of the participants who reported low prior knowledge. However, it can be that the introductory knowledge they have has allowed them to develop basic schemata about the topic, which causes the differences in learning outcomes from different instructional materials.

6.3 Effect of prior cognitive load on instructional efficiency

The cognitive load caused by previous tasks can limit the available cognitive resources, as they are only replenished by rest [CK20, CCAPS18]. Thus we expected that participants who reported high cognitive load prior to taking part in the study would benefit from the limited intrinsic cognitive load of high abstraction level.

Our expectations were proven wrong. Participant's ratings of their mental effort expended prior to the test did not have any effect on the instructional efficiency. High physical effort expended prior to the test increased the instructional efficiency, which can be explained by exercise helping to replenish cognitive resources and thus leading to lower cognitive load later on.

High cognitive load on answering the pre-test questionnaire leads to worse instructional efficiency. There was no difference between the treatment conditions, which indicates that no type of instructional material was better or worse for participants with high pre-test cognitive load. Our data suggest that high pre-test cognitive load does not lead to worse test results, but leads to higher study- and test cognitive load.

One possible explanation for this are environmental factors. We did not measure the participants' study environment. There might have been factors in the study environment of participants with high pre-test cognitive load, which increased cognitive load (distractions or sounds, for example), which would lead to higher cognitive load throughout the test.

Individual differences in personality, learning styles, and learning preferences also affect cognitive load [PKL10]. Further research is needed to understand why participants who reported high cognitive load answering the pre-test questionnaire reported high test- and study cognitive load as well with no instructional material performing better or worse for them.

7 Threats to Validity

Assessing the internal validity of our study, we have identified some possible threats to our validity. Firstly, the study material was embedded in the existing online instructional material of a programming course. The existing material had a small number of static visualizations and no responsive visualizations, so the study material was different than the material the participants were used to. This may have caused some participants to reject the new type of material or cause confusion on how to learn from and use the new type of material. This might account for some of the effects we identified.

Secondly, we were not able to study how the participants used the material. We can not know if the participants carefully studied the material as was expected or if they, for example, browsed the material for answers to the quizzes and then quickly continued after receiving the points from the questionnaire. The responsive visualizations do not allow quick browsing quite as well as text, so if the participants used this kind of study method, the responsive visualizations would not perform well for them. We also did not measure time on task, or how long participants spent studying the provided instructional material. Differences in time on task might account for some of the effects we identified.

Thirdly, the study was done in a real-life setting. A multitude of factors such as study environment, motivation, attitude towards the material, and feelings affect learning. We did not measure these factors in this study.

Also, the abstraction levels we used for this study were defined by us for this study. Although the instructional material was tested and evaluated by our colleagues prior to the study, the differences between the instructional efficiency of the abstraction levels can partially be explained by differences in the material design. More research would be needed to define the abstraction levels conclusively

Looking at the external validity of our study, the way we calculated instructional efficiency could be a threat to our validity. We used instructional efficiency as a measure of the performance of the instructional material. The instructional efficiency is calculated from test cognitive load, study cognitive load, and test results. High study cognitive load leads to lower instructional efficiency. However, the formula does not differentiate between the different types of cognitive load. Germane cognitive load, cognitive load caused by processing information, is beneficial to studying. High study cognitive load can, in some situations, be germane cognitive load, and thus high study cognitive load does not always mean ineffective learning. We did not measure the different types of cognitive loads, so we were not able to assess whether high study cognitive load in some situations could be attributed to beneficial germane cognitive load.

8 Conclusions

The purpose of this thesis was to investigate the compound effect of engagement and abstraction on the instructional efficiency of online instructional material in the context of a university programming course. By determining how different types of instructional materials perform overall and for students with different prior knowledge levels and different levels of cognitive load before studying, we aimed to create insight into how these different ways to present information perform in a real-life context. Our research questions were as follows:

RQ1 How do engagement and abstraction together affect the instructional efficiency of instructional material?

RQ2 Does prior knowledge on the topic being studied affect the instructional efficiency of instructional material?

RQ3 How does cognitive effort expended prior to studying affect the instructional efficiency of instructional material?

We conducted a study comparing two different abstraction levels and three different engagement levels across two experiments to answer our research questions. The answers to our research questions were:

How do engagement and abstraction together affect the instructional efficiency of instructional material?

The study revealed that overall there were no statistically significant differences between the instructional efficiency of the different instructional materials.

Does prior knowledge on the topic being studied affect the instructional efficiency of instructional material?

Participants' self-reported prior knowledge had a significant effect on instructional efficiency. High prior knowledge, or a high percentage of correct answers in the pre-test questionnaire on the topic studied in the experiment, raised instructional efficiency for all treatment condition groups. We also measured significant differences between the instructional efficiency of the different treatment condition groups within each experiment. In the experiment where participants studied instructional material on a topic they had already been introduced to, high abstraction no viewing condition performed the best. In the experiment where participants studied an entirely new topic, responding conditions performed the best, and we measured lower study cognitive load on the lower abstraction level.

How does cognitive effort expended prior to studying affect the instructional efficiency of instructional material?

Participants' mental effort within the last hour before the test did not significantly affect the instructional efficiency, but physical exertion did raise the instructional efficiency universally for all treatment condition groups. High pre-test cognitive load, or high cognitive load answering the pre-test questionnaire, lowered instructional efficiency universally for all treatment condition groups. High pre-test cognitive load raised study cognitive load and test congnitive load, but did not lower the test results.

Further research into the efficiency of instructional materials in learning programming is needed. For example, the engagement taxonomy used in our work stemmed from research into program visualizations, and our research highlights the need to study it further in learning programming. To our knowledge, this study has been the first study in computing education research specific to learning programming that attempts to quantify the compound effect of abstraction and engagement, opening new directions for research. Our results indicate that differences in students' knowledge levels do affect the instructional efficiency of different abstraction and engagement levels. However, the effect is different when knowledge level is measured as correct answers to topic-specific questions prior to studying or as a self-reported level of knowledge. Further research into quantifying students' prior knowledge and mapping it to appropriate learning materials could be beneficial. Similarly, our results on the effect of pre-test cognitive load on instructional efficiency should be studied further. We do not know if the pre-test cognitive load highlighted previous cognitive load in some way that the NASA-TLX instrument did not, or if there are other factors that contributed to the outcomes.

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Appendix 1. Cognitive load effects on Instructional material

Cognitive load effects on Instructional material	
Reducing extraneous cognitive load	
The goal free effect	It is less cognitively demanding to ask learners to find any possible solution or as many possible solutions to a problem than to ask them for one specific solution [VGP08].
The Worked-Examples Effect	For novice learners, studying worked examples has been proven to be more effective than solving equivalent problems [SVMP98].
The Split-Attention Effect	Instructional material presented in split-attention format, where different information sources have to be integrated in order to understand them. This increases extraneous cognitive load when compared to physically integrated formats. [Swe10]
The Redundancy Effect	Presenting multiple sources containing the same information has been shown to hamper learning in comparison to presenting the information only once [vMJKK12].
The Modality Effect	Effective working memory capacity can be increased by using both visual and auditory working memory rather than either processor alone [SvMP19].
Increasing germane cognitive load	

Presentation of Multiple Examples	Presenting several examples allows learners to compare between them. Learners learn to abstract across irrelevant example features, which is prerequisite for schema construction [vMJKK12].
Incomplete Examples	Providing learners with partially worked-out examples allows them to engage in self-explaining to anticipate the missing steps, which increases learning outcomes [vMJKK12].
Fading Instructional Support	With increasing expertise the learner is able to self-explain missing steps. Fading instructional support overtime decreases the expertise reversal effect as redundant support is faded away as the expertise of the student increases [vMJKK12].
Emphasizing Sub-Goal Structure	Illustrating the sub-goal structure of worked examples allows learners to self-explain why certain steps belong together and which goal is achieved by applying which step. Self-explaining the learning content results in increased germane cognitive load [vMJKK12].
Managing intrinsic cognitive load	
Simple-to-Complex Strategy	Highly complex material with many interacting elements can be split up so that the elements can be processed serially [vMJKK12].

Low-to-High-Fidelity Strategy	High-fidelity environments and materials contain more interacting elements than low- fidelity environments and materials. It is possible to gradually increase the number of interactive information elements by gradually increasing the fidelity of the material. [vMJKK12]

Appendix 2. NASA-TLX (original)

Below is the original NASA-TLX questionnaire used to measure subjective workload.

Figure 8.6

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

Appendix 3. NASA-TLX (Finnish translation)

Arvioi viimeisen tunnin aikana suorittamiesi toimintojen rasittavuus.

HENKINEN VAATIMUSTASO

Oliko tehtävä helppo ja yksinkertainen vai vaativa ja monimutkainen? Kuinka paljon tehtävä vaati päätöksentekoa, ajattelua, etsimistä, muistamista, laskemista jne.? VÄHÄN PALJON

FYYSINEN VAATIMUSTASO Kuinka paljon tehtävä vaati fyysistä toimintaa, esim. kantamista, nappien painamista jne.? VÄHÄN 1 2 3 4 5 6 7 8 9 10 PALJON

AJALLINEN VAATIMUSTASO Oliko tehtävä hidas-, sopiva- vai nopearytminen? Kuinka paljon aikapainetta tunsit tehtävän aikana? VÄHÄN 1 2 3 4 5 6 7 8 9 10 PALJON

SUORITUS Kuinka tyytyväinen olet toimintaasi tavoitteiden saavuttamisessa? Kuinka hyvin mielestäsi saavutit tehtävän tavoitteet? HYVIN 1 2 3 4 5 6 7 8 9 10 HEIKOSTI

PONNISTELU Kuinka paljon sinun täytyi ponnistella henkisesti ja fyysisesti tehtävän aikana? VÄHÄN 1 2 3 4 5 6 7 8 9 10 PALJON

TURHAUTUMINEN Olitko rasittunut ja turhautunut tehtävän suorituksen aikana? VÄHÄN 1 2 3 4 5 6 7 8 9 10 PALJON

Appendix 4. Pre-test questionnaire for Hash Tables (Finnish

1. Kuinka paljon tiedät hajautustauluista?

    (a) En yhtään mitään

    (b) Olen joskus kuullut niistä, mutta en ole koskaan käyttänyt niitä

    (c) Olen käyttänyt hajautustauluja, ja tiedän miten ne toimivat

2. <avain, arvo> -parin paikka hajautustalussa määräytyy minkä mukaan?

    (a) avaimen

    (b) avaimen hajautusarvon

    (c) arvon hajautusarvon

3. Miten hajautustaulu toteutetaan Javassa?

    (a) taulukkona

    (b) taulukkona, jonka jokainen alkio sisältää listan

    (c) listana, joka sisältää taulukkoja

4. Mikä on hajautusfunktion rooli hajautustaulun käytössä?

    (a) Yhdistää avain oikeaan arvoon

    (b) Etsiä <avain, arvo> -pari listasta

    (c) Päätellä, mihin listaan <avain, arvo> -pari talletetaan

Appendix 5. Multiple choice questionnaire for Hash Tables (Finnish)

1. Ajattele äsken opiskelemaasi materiaalia, miten arvioisit oppimateriaalin?
    (a) Helposti ymmärrettävä ja selkeä
    (b) Paikoittain hankalasi ymmärrettävä, mutta kuitenkin riittävän selkeä
    (c) Hyvin hankalasti ymmärrettävä, ei yhtään selkeä
2. <avain, arvo> -parin paikka hajautustalussa määräytyy minkä mukaan?
    (a) avaimen
    (b) avaimen hajautusarvon
    (c) arvon hajautusarvon
3. Ajattele juuri opiskelemaasi materiaalia hajautustauluista. Miksi <avain, arvo> -parien tallettaminen hajautustaulun sisällä lyhyinä listoina on hyödyllistä?
    (a) Se tekee uusien parien lisäämisestä nopeampaa
    (b) Se vie vähemmän muistitilaa
    (c) On nopeampaa käydä läpi lyhyt lista kuin pitkä lista arvoa etsittäessä.
4. Milloin hajautustaulun käyttäminen EI ole hyvä idea?
    (a) Kun on tärkeää, että tieto voidaan käydä läpi juuri tietyssä järjestyksessä.
    (b) Kun sinulla on liikaa, esimerkiksi tuhansia, <avain, arvo> -pareja talletettavaksi.
    (c) Kun sinun täytyy voida löytää tietty arvo nopeasti

Appendix 6. Pre-test questionnaire for multidimensional arrays (Finnish

1. Kuinka paljon tiedät moniuloitteisista taulukoista?
   (a) En yhtään mitään
   (b) Olen joskus kuullut niistä, mutta en ole koskaan käyttänyt niitä
   (c) Olen käyttänyt moniuloitteisia taulukkoja, ja tiedän miten ne toimivat
2. Miten moniuloitteiset taulukot toteutetaan Javassa?
   (a) listoina, jotka sisältävät taulukkoja
   (b) listoina, jotka sisältävät listoja
   (c) taulukkoina, jotka sisältävät taulukkoja
3. Miten tietty arvo haetaan moniuloitteisesta taulukosta?
   (a) käymällä läpi kaikki talletetut arvot
   (b) Jos arvon indeksi tiedon jokaisessa ulottuvuudessa on tiedetty, arvo voidaan hakea näiden indeksien perusteella.
   (c) Käymällä läpi kaikki arvot tiedon tietyssä ulottuvuudessa
4. Mikä seuraavista on esimerkki kaksiuloitteisesta tiedosta?
   (a) Kaikkien pyydystettyjen kalojen paino
   (b) Kaikkien pyydystettyjen kalojen paino niiden pyydystäneen kalastajan mukaan
   (c) Kaikkien pyydystettyjen kalojen paino niiden pyydystäneen kalastajan ja vuorokaudenajan mukaan

Appendix 7. Multiple choice questionnaire for multidimensional arrays (Finnish)

1. Ajattele äsken opiskelemaasi materiaalia, miten arvioisit oppimateriaalin?
   (a) Helposti ymmärrettävä ja selkeä
   (b) Paikoittain hankalasi ymmärrettävä, mutta kuitenkin riittävän selkeä
   (c) Hyvin hankalasti ymmärrettävä, ei yhtään selkeä
2. Javassa moniuloitteiset taulukot ovat?
   (a) Taulukoita, joiden jokainen alkio sisältää taulukon.
   (b) Listoja, jotka sisältävät taulukoita
   (c) Listoja, jotka sisältävät listoja
3. Mikä seuraavista on esimerkki kaksiuloitteisesta tiedosta?
   (a) Yhden oppilaan kaikki tehtäväpisteet
   (b) Luokan kaikkien opiskelijoiden koetulokset
   (c) Opiskelijoiden koetulokset heidän syntymävuotensa mukaan
4. Miten tietyn arvon löytäminen moniuloitteisesta taulukosta eroaa tietyn arvon löytämisestä hajautustaulusta?
   (a) Moniuloitteista taulukkoa käytettäessä on aina käytävä läpi monta taulukkoa, kun taas hajautustaulua käytettäessä tulee käydä läpi vain lyhyt lista.
   (b) Jos arvon indeksit ovat tiedossa, sen voi hakea moniuloitteisesta taulukosta käymättä läpi mitään, mutta hajautustaulua käytettäessä on aina käytävä läpi lista kaikista <avain, arvo> -pareista, joilla on sama hajautusarvo.
   (c) Hajautustaulua käytettäessä, jos avaimen hajautusarvo on tiedossa, sen arvon voi hakea hajautustaulusta käymättä läpi mitään, mutta moniuloitteisia taulukoita käytettäessä on aina käytävä läpi monta taulukkoa tietyn arvon löytämiseksi.